

Labor Income Risk and Asset Returns*

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Abstract

This paper shows, from the consumer's budget constraint, that expected future labor income growth rates and the residuals of the cointegration relation among log consumption, log asset wealth and log current labor income (summarized by the variable *cay* of Lettau and Ludvigson (2001a)), should help predict U.S. quarterly stock market returns and explain the cross-section of average returns. I find that *a)* fluctuations in expected future labor income are a strong predictor of both real stock returns and excess returns over a Treasury bill rate, *b)* when this variable is used as conditioning information for the Consumption Capital Asset Pricing Model (CCAPM), the resulting linear factor model explains four fifth of the variation in observed average returns across the Fama and French (25) portfolios and prices correctly the small growth portfolio. The paper also finds that about one third of the variance of returns is predictable, over a horizon of one year, using expected future labor income growth rates and *cay* jointly as forecasting variables.

Keywords: Human Capital, Labor Income Risk, Expected Returns, Consumption Capital Asset Pricing Model. *JEL Classification:* E21, E24, G12.

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1 Introduction

This paper uses the representative consumer's budget constraint to derive an equilibrium relation between expected future labor income growth rates – summarized by the variable lr – and expected future asset returns. Moreover, it shows that the empirical counterpart of these expected changes in labor income (\widehat{lr}) carries relevant information for predicting future asset returns and explaining the cross-section of average returns.

Lettau and Ludvigson (2001a, 2001b) use the budget constraint to show that the residuals of the cointegration relation among log consumption, log asset wealth and log current labor income (summarized by the variable cay), should predict asset returns. This paper builds on their approach and shows that cay and lr should jointly predict future asset returns. Moreover, since lr captures the movements in human capital due expected changes in labor income, only considering the two variables together provides an appropriate proxy for the log consumption to total wealth ratio.

In the major industrialized countries, roughly two thirds of overall wealth consists of claims on non-traded labor incomes. To the extent that investors hedge against adverse fluctuations in labor income, the mere size of human capital in total wealth makes its potential impact on equilibrium asset prices large. Expected changes in future labor income growth rates map into changes for the market value of human capital, therefore movements in lr capture a relevant state variable and source of risk.

The main finding of the paper is that \widehat{lr} has high predictive power for future asset returns and, when used as conditioning information for the Consumption Capital Asset Pricing Model (CCAPM), it delivers a linear factor model that rivals the Fama and French (1993) and the Lettau and Ludvigson (2001b) three-factor models in explaining the cross-section of expected returns of the Fama and French size and book-to-market portfolios. In addition, the conditional factor model proposed prices correctly the small growth portfolio and performs well in explaining the cross-section of expected returns of several other portfolios data sets. Moreover, using cay and lr jointly as predictors and conditioning information, about one third of the variance of returns is

predictable over a horizon of one year and more than four fifth of the cross-sectional variation in expected returns of the Fama and French portfolios is explained.

What drives the results? In the data, expectations of high future labor income growth are associated with lower stock market excess returns, and low labor income growth expectations are associated with higher than average excess returns, suggesting that the success of lr as predictor of asset returns and conditioning variable is due to its ability to track time varying risk premia.

I show that these results are consistent with the fact that high lr represent a state of the world in which agents expect to have abundance of resources in the future to finance consumption, therefore low returns on asset wealth are feared less and lower equilibrium risk premia are required. Moreover, these findings are consistent with a Kreps-Porteus-Epstein-Zin-Weil preferences framework where consumption growth and dividend growth share a small predictable component, as in Bansal and Yaron (2004), and this component is the predictable part of future labor income growth.

The empirical results presented are also checked for potential spurious regression problems and "look-ahead" bias, and appear to be robust to these issues. Moreover, reduced form *VAR* exercises confirm that labor income has high marginal predictive power for market returns.

The research presented in this paper is indebted in particular to the work of Campbell and Shiller (1988) on the relation between the log-dividend price ratio and expected future returns, and the works of Campbell and Mankiw (1989) and Lettau and Ludvigson (2001a, 2001b) on the implication of the consumer's budget constraint for asset pricing.

More generally, the paper builds on the large literature on predictability and cross-section of asset returns. The main results are most closely related to Jagannathan and Wang (1996), Jagannathan, Kubota, and Wang (1996) and Palacios-Huerta (2003) on the human capital augmented Capital Asset Pricing Model (CAPM); to Santos and Veronesi (2003) that find that the labor income to consumption ratio forecasts asset returns and is a good conditioning variable for the CAPM; and to Constantinides

and Duffie (1996), Heaton and Lucas (1996), Davis and Willen (2000), Storesletten, Telmer, and Yaron (2001) and Wei (2003), on the relation between labor income risk and market returns.

The balance of the paper is organized as follows. Section 2 uses the consumer's budget constraint to derive an equilibrium relation between expected future labor income growth and asset returns. Sections 3, 4, 5 and 6 tests the implication of the relation derived in section 2. In particular, section 3 focuses on predicting asset returns, section 4 looks at the predictability of consumption growth, section 5 presents a reduced form Vector Autoregressive Model (*VAR*) that confirms the high marginal predictive power of labor income for market returns, and section 6 studies the cross-section of average asset returns of the Fama and French size and book-to-market portfolios and of several other data sets of portfolios. Section 7 rationalizes the results of the previous sections by showing that movements in \widehat{lr} are associated with time variations in risk premia and provides a structural models, based on the work of Bansal and Yaron (2004), consistent with the outlined features of the data.

2 Why should labor income risk matter?

This section uses the consumer's budget constraint and the link between human capital and labor income to develop an equilibrium relation between expected future labor income growth and future asset returns.

First, as in Campbell (1996) and Jagannathan and Wang (1996), labor income (Y_t) can be thought of as the dividend on human capital (H_t). Under this assumption we can define the return to human capital as

$$1 + R_{h,t+1} = \frac{H_{t+1} + Y_{t+1}}{H_t}.$$

Log-linearizing this relation around the steady state under the assumption that the steady state human capital-labor income ratio is constant ($Y/H = \rho_h^{-1} - 1$, where

$0 < \rho_h < 1$)¹, we get

$$r_{h,t+1} = (1 - \rho_h) k_h + \rho_h (h_{t+1} - y_{t+1}) - (h_t - y_t) + \Delta y_{t+1} \quad (1)$$

where $r := \log(1 + R)$, $h := \log H$, $y := \log Y$, k_h is a constant of no interest, and the variables without time subscript are evaluated at their steady state value. Therefore, assuming that $\lim_{i \rightarrow \infty} \rho_h^i (h_{t+i} - y_{t+i}) = 0$, the log human capital income ratio can be rewritten as a linear combination of future labor income growth and future returns on human capital

$$h_t - y_t = \sum_{i=1}^{\infty} \rho_h^{i-1} (\Delta y_{t+i} - r_{h,t+i}) + k_h. \quad (2)$$

This last equation tells us that the log human capital to labor income ratio has to be equal to the discounted sum of future labor income growth and human capital returns. Moreover, this equation is similar, both in structure and interpretation, to the relation between the log dividend-price ratio and future returns and dividends derived by Campbell and Shiller (1988):² taking time t conditional expectation of both sides of equation (2) we have that when the log human capital to labor income ratio is high, agents should expect high future labor income growth or low human capital returns.

Second, defining C_t as time t consumption, W_t as the aggregate wealth (given by human capital plus asset holdings) and with $R_{w,t+1}$ the return on wealth between period t and $t + 1$, the consumer's budget constraint can be written as

$$W_{t+1} = (1 + R_{w,t+1}) (W_t - C_t). \quad (3)$$

¹Baxter and Jermann (1997) calibrates $Y/H = 4.5\%$ implying $\rho^h = 0.955$

²Campbell and Shiller (1988), defining the log return of an asset as

$$r_t = \log(P_t + D_t) - \log P_{t-1},$$

(where P and D are, respectively, price and dividend of the asset) derive the relation

$$d_t - p_t = E_t \sum_{i=1}^{\infty} \rho^{i-1} (r_{t+i} - \Delta d_{t+i}) + k_d$$

where $d := \log d$ and $p := \log P$.

Campbell and Mankiw (1989) show that equation (3) can be approximated by Taylor expansion obtaining (under the assumption that the consumption-wealth ratio is stationary and that $\lim_{i \rightarrow \infty} \rho_w^i (c_{t+i} - w_{t+i}) = 0$, where $\rho_w = (W - C) / W < 1$)

$$c_t - w_t = \sum_{i=1}^{\infty} \rho_w^i r_{w,t+i} - \sum_{i=1}^{\infty} \rho_w^i \Delta c_{t+i} + k_w \quad (4)$$

where $c := \log C$ and k_w is a constant. The aggregate return on wealth can be decomposed as

$$R_{w,t+1} = v_t R_{a,t+1} + (1 - v_t) R_{h,t+1}$$

where v_t is a time varying coefficient and $R_{a,t+1}$ is the return on financial wealth. Campbell (1996) shows that we can approximate this last expression as

$$r_{w,t} = v r_{a,t} + (1 - v) r_{h,t} + k_r \quad (5)$$

where k_r is a constant, v is the mean of v_t and $r_{w,t}$ is the log return on total wealth. Moreover, we can approximate the log total wealth as

$$w_t = v a_t + (1 - v) h_t + k_a \quad (6)$$

where a_t is the log asset wealth and k_a is a constant.

Substituting equations (6), (2) and (5) into (4) we get

$$\begin{aligned} c_t - v a_t - (1 - v) \left(y_t + \sum_{i=1}^{\infty} \rho_h^{i-1} \Delta y_{t+i} \right) &= \sum_{i=1}^{\infty} \rho_w^i (v r_{a,t+i} - \Delta c_{t+i}) \\ &\quad + (1 - v) \sum_{i=1}^{\infty} (\rho_w^i - \rho_h^{i-1}) r_{h,t+i} + k \end{aligned}$$

where k is a constant. The left hand side of this equation is the log consumption-aggregate wealth ratio expressed as function of only observable variables, and its last term measures the contribution of future labor income growth to the current value of human capital. This equation holds ex-post as a direct consequence of agent's budget constraint, but it also has to hold ex-ante. Taking time t conditional expectation of both sides and assuming that y_t follows an ARIMA process with innovations indicated

by ε_t , we have that

$$cay_t - (1 - v)lr_t = E_t \sum_{i=1}^{\infty} \rho_w^i (vr_{a,t+i} - \Delta c_{t+i}) + \eta_t + k \quad (7)$$

where $lr_t := \psi(L)\varepsilon_t = E_t \sum_{i=1}^{\infty} \rho_h^{i-1} \Delta y_{t+i}$ represent the discounted expected growth in future labor income,³ $\eta_t := (1 - v) E_t \sum_{i=1}^{\infty} (\rho_w^i - \rho_h^{i-1}) r_{h,t+i}$ is a stationary component and, following Lettau and Ludvigson (2001a, 2001b), $cay_t := c_t - va_t - (1 - v)y_t$.

When the left hand side of equation (7) is high, consumers expect either high future returns on market wealth or low future consumption growth. The lr_t term measures the contribution of future labor income growth to the state variable h_t , therefore capturing the expected long run wealth effect of current and past labor income shocks.⁴

For a constant cay_t and expected future consumption growth, equation (7) tells us that if agents expect their labor income to grow in the future (high lr_t), the equilibrium return on asset wealth will be lower. One interpretation is that high lr_t represent a state of the world in which agents expect to have abundance of resources in the future, therefore low returns on asset wealth are feared less.

It is worth comparing equation (7) with a similar one obtained by Lettau and Ludvigson (2001b)

$$cay_t = E_t \sum_{i=1}^{\infty} \rho_w^i (vr_{a,t+i} - \Delta c_{t+i}) + \tilde{\eta}_t + \tilde{k} \quad (9)$$

³ $\psi(L)$ is a polynomial in the lag operator.

⁴Moreover, if we follow Campbell and Shiller (1988) and approximate the log return on human capital as

$$r_{h,t+1} = r + (E_{t+1} - E_t) \sum_{i=1}^{\infty} \rho_h^{i-1} \Delta y_{t+i}$$

we have from equation (2) that the log human capital will depend only (disregarding constant terms) on current and future expected labor income

$$h_t = y_t + E_t \sum_{i=1}^{\infty} \rho_h^{i-1} \Delta y_{t+i}, \quad (8)$$

therefore the human capital wealth level will vary as expectations of future labor income change.

where \tilde{k} is a constant and $\tilde{\eta}_t$ is an error component. Based on this equation, Lettau and Ludvigson (2001a) argue that cay_t should be a good proxy for market expectations of future asset returns ($r_{a,t+i}$) and future consumption growth as long as human capital returns are not too variable.⁵ When cay in equation (9) is high, the authors argue, agents must be expecting either high future returns on the market portfolio or low consumption growth rate. Comparing equation (7) with equation (9), it is clear that consumption can also be high as consequence of an expected increases in future labor income. Nevertheless, the argument of Lettau and Ludvigson (2001a) applies to the *total* log consumption wealth ratio $cay - (1 - v)lr$ (where lr captures changes in human capital wealth due to expected future changes in labor income): when this ratio is high agents must be expecting either high market returns or low consumption growth.

The budget constraint in equation (7) can be combined with various models of consumer behavior, and in this case the labor income risk component will influence equilibrium asset prices and returns. Moreover, the presence of labor income innovation on the left hand side of equation (7) can be consistent with excess smoothness of consumption. A negative labor income shock increases the left hand side of equation (7). If labor income innovations were uncorrelated with future asset returns, agents would have to reduce future and current consumption. If instead current labor income innovations are negatively correlated with future asset returns, consumption will need to be reduced less than proportionally in reaction to the shock. Indeed, the estimations reported in the next section show that $corr(lr_t, r_{a,t+s}^i)$ is negative for $s > 0$ implying that, to satisfy the budget constraint, household consumption needs to respond less

⁵Lettau and Ludvigson (2004) are aware that future expected labor income growth should in principle be added to equation (9) but they argue that, if labor income follows a random walk, this component can be neglected and cay provides an appropriate proxy for the consumption-wealth ratio. Nevertheless, if labor income is far from being a random walk and its growth rates are predictable (as section 5 shows), lr should be added to cay (as in equation (7)) to obtain an accurate proxy for the consumption-wealth ratio.

than proportionally to changes in expected future income.

Since lr_t captures movements in a relevant state variable - the level of human capital - it is likely to have an influence on equilibrium asset returns. Moreover, following the same line of argument as in Lettau and Ludvigson (2001a, 2001b), equation (7) suggests that the labor income risk term (lr) should to some extent *i*) forecast predictable changes in asset returns, *ii*) be an appropriate conditioning variable for the capital asset pricing model since it captures time-varying expectation of future labor income in the economy. Both implications are analyzed in the next sections.

3 Does labor income risk help in forecasting stock market returns?

This section explores the time series relation between the labor income risk factor and stock returns. lr_t is used as predictor of future asset returns and its empirical performance is compared to two benchmarks: the forecasting ability of cay_t (a well known good predictor of market returns) and lagged asset returns.

In assessing the forecasting ability of lr_t one faces several econometric issues. First, Ferson, Sarkissian, and Simin (2002) argue, with a simulation exercise, that if both *expected* returns and the predictive variable are highly persistent the in-sample regression results may be spurious, and both R^2 and statistical significance of the regressor are biased upward.⁶ The autocorrelation of realized returns is low in the data,⁷ nevertheless the degree of persistence of *expected* returns is not observable.⁸ Since $lr_t = \psi(L)\varepsilon_t$ is autocorrelated by construction, this could give rise to spurious regression results. As a

⁶See also Torous, Valkanov, and Yan (2005).

⁷The autocorrelations of the realized CRSP-VW and S&P 500 stock returns are, respectively, 0.07 and 0.09.

⁸The return may be considered to be sum of an unobservable expected return plus a unpredictable noise, and the predictable component could be highly autocorrelated.

consequence, both in-sample and out-of-sample prediction are performed.⁹ Moreover, coherently with equation (7), cay_t is added as additional predictor to check whether it drives out the statistical significance of lr_t . In addition, we explore the explanatory power of the estimated labor income innovation ($\hat{\varepsilon}_t$) alone, since its time series is serially uncorrelated.

Second, a "look-ahead" bias might arise from the fact that the coefficients used to generate the empirical counterpart of lr_t are estimated using the full data sample. To address this issue we also look at out of sample forecasts where the lr_t is estimated using only *prior* data on labor income, since this approach removes the danger of a "look-ahead" bias.¹⁰ Moreover, section 5 shows, with a *VAR* exercise, that the joint estimation of the forecasting equations for labor income and market returns implies that labor income has a lot of marginal predictive power for returns.

Table 1 shows the results of using the empirical estimates of lr_t and cay_t (\hat{lr}_t and \widehat{cay}_t), and lagged market returns as predictive variables for future market returns.¹¹ Panel A reports measures of fit and estimated coefficients of the in-sample predictive regressions and *MRSE* and pseudo R^2 of out-of-sample forecasts, for the one-quarter-ahead to one-year-ahead real returns on the CRSP-VW market return index ($r_{t,t+1}$ to $r_{t,t+4}$). Panel B instead focuses on forecasting excess returns ($r_{t,t+1}^e$ to $r_{t,t+4}^e$). The regressions are performed using quarterly data and the sample period, 1952:04 to 2001:4, is the longest possible given the available data and the desire to keep a

⁹Inoue and Kilian (2002) demonstrate that in-sample and out-of-sample tests of predictability are, under the null of no predictability, asymptotically equally reliable.

¹⁰On the other hand, as argued in Lettau and Ludvigson (2002), this approach can strongly understate the predictive ability of the regressor since, in shorter samples, it would be less precisely estimated.

¹¹ $\hat{lr}_t = \psi(L)\hat{\varepsilon}_t$ is constructed assuming that the log labor income follows an ARIMA process. The selected model is a MA(2) in the first difference (as in Davis and Willen (2000)). Therefore, lr_t is the linear combination of labor income shocks at time t and $t - 1$. Details on the estimation of $\hat{\varepsilon}_t$ and \hat{lr}_t are reported in section 2 of the Appendix. The time series of \widehat{cay}_t is taken from Sidney Ludvigson's homepage: <http://www.econ.nyu.edu/user/ludvigsons/>

fixed sample size for both short and long horizon returns. To construct out-of-sample forecasts, the predictive regressions are estimated recursively using data from the first available observation to the quarter immediately preceding the forecast period. The first out-of-sample forecast period is 1962:04,¹² and the forecast performance is evaluated by comparing the mean squared error from the set of one-step-ahead forecasts and the pseudo R^2 .¹³

The first two rows of each panel reports R^2 and \bar{R}^2 of the forecasting *OLS* regressions. The last two rows reports root mean square error (*RMSE*) and the pseudo R^2 . The remaining rows reports the estimated coefficients of the in-sample regressions and (in parenthesis) their standard errors. All regressions use Newey-West correction (Newey and West (1987)) of the standard errors for generalized serial correlation of the residuals.¹⁴

The first column of Panel A reports the regression of $r_{t,t+1}$ on the first lag of the dependent variable ($r_{t-1,t}$). The regressor has a very low predictive power (it predicts less than 1 percent of next quarter variation in real returns) and is not statistically significant. The forecasting power of $r_{t-1,t}$ becomes even weaker as we increase the horizon over which future returns should be predicted (columns 5, 9 and 13): for $r_{t,t+2}$ to $r_{t,t+4}$ the R^2 is basically zero, the regressor is never statistically significant and the estimated slope coefficient reduces with the horizon.

The second column of Panel A reports the regression of $r_{t,t+1}$ on \widehat{lr}_t . The regressor predicts 5 percent of next quarter variation in real returns, it is strongly statistically significant and has negative sign coherently with equation (7). The predictive impact of \widehat{lr}_t is also economically large: the point estimate of the coefficient is -2.20. The labor income is used to compute \widehat{lr}_t is in per-capita term and \widehat{lr}_t has a standard deviation of 0.01. Thus, a one-standard-deviation decrease in the expected future labor income growth leads to 220 basis points rise in the expected real return on the CRSP-VW

¹²This allows to first estimate each forecasting equation using the first ten years of available data.

¹³The pseudo R^2 is defined as one minus the ratio of MSE from a forecast model to the benchmark model of constant returns.

¹⁴Similar results are obtained using Hansen and Hodrick (1980) standard errors.

market return index. The forecasting power of \widehat{lr}_t grows as we increase the horizon (columns 6, 10 and 14) over which future returns are predicted, explaining up to 16 percent of the variability in future market returns at one year horizon. The estimated slope coefficients are consistently negative, significant and increase with the horizon. \widehat{lr}_t also shows a good out-of-sample predictive power, with a pseudo R^2 that increases in magnitude with the horizon, from 4 percent (for $r_{t,t+1}$) to 15 percent (for $r_{t,t+4}$), suggesting that the in-sample results are unlikely to be spurious.

For comparison, the ability of \widehat{cay}_t to forecast $r_{t,t+1}$ is tested in column 3 of Panel A. \widehat{cay}_t predicts 8 percent of next quarter variation in real returns and the estimated regression coefficient is both economically and statistically significant (a one-standard-deviation increase in \widehat{cay}_t predicts a 195 basis points increase in expected real returns). The forecasting ability of \widehat{cay}_t grows with the horizon (columns 7, 11 and 15), and at the four quarters horizon it explains 26 percent of the variability in future market returns. The out-of-sample performance is also very good, with a pseudo R^2 that grows with the horizon from 8 percent to 24 percent at one year horizon.

Columns 4, 8, 12 and 16 of Panel A explores the joint predictive ability of \widehat{lr}_t and \widehat{cay}_t that, as the budget constraint (7) suggests, should do best. The measures of fit always increase significantly with respect to the univariate regressions and the two variables are able to explain from 11 percent (at the one quarter horizon) to 32 percent (at the four quarters horizon) of the variability in returns. The regressors are always individually and jointly significant. The estimated coefficients are somehow smaller than the ones of the univariate regressions but the reduction is not statistically significant. The out-of-sample predictive power of the joint regressors is also remarkable, with a pseudo R^2 that ranges from 10 percent (at one quarter horizon) to 30 percent (at one year horizon).

Panel B of Table 1 focuses on forecasting excess returns defined as the difference between the CRSP-VW market return index and the three month Treasury bills. Again, lagged returns have little if any predictive power and the estimated coefficient on the regressor is neither statistically nor economically significant at any of the horizons

considered. The predictive power of \widehat{lr}_t is again quite high: between 5 percent (at one quarter horizon) and 17 percent (at the one year horizon) of the variability in market excess returns is captured by this regressor. The estimated regression coefficients are always significant and extremely similar in magnitude to the ones in Panel A. The out-of-sample performance is also good, with a pseudo R^2 that ranges from 4 percent (at one quarter horizon) to 15 percent (at one year horizon). \widehat{cay}_t alone too is able to explain a substantial share of the variability of excess returns (between 7 percent at the one quarter horizon to 23 percent at one year horizon), the estimated regression coefficients are always significant and it has good out-of-sample predictive power (with a pseudo R^2 that ranges from 7 percent to 21 percent). \widehat{lr}_t and \widehat{cay}_t jointly are able to explain from 10 percent (at one quarter horizon) to 31 percent (at one year horizon) of the variation in excess returns and the pseudo R^2 ranges from 8 to 27 percent. Moreover, the regressors are both individually and jointly significant at any horizon considered and the slope coefficients are not statistically different from the ones obtained in the univariate regressions.

The findings suggest that both variables have significant predictive ability and that they predict different components of the stochastic process of market returns, since in the joint regressions they are both strongly statistically significant, and both in-sample and out-of-sample measures of fit are much larger than in the univariate regressions (the minimum increase in \bar{R}^2 , moving from the univariate regressions to the multivariate ones, ranges from 2 percent to 8 percent, and the minimum increase in pseudo R^2 ranges from 1 percent to 6 percent).

Since $\widehat{lr}_t = \psi(L)\widehat{\varepsilon}_t$ is autocorrelated by construction, this could give rise to spurious in-sample regression results.¹⁵ As a robustness check Table 2 looks at the predictive ability of $\widehat{\varepsilon}_t$ and $\widehat{\varepsilon}_{t-1}$ (since \widehat{lr}_t is a linear combination of this two estimated innovation of the labor income process).

The table shows that both $\widehat{\varepsilon}_t$ and $\widehat{\varepsilon}_{t-1}$ perform well as predictors in the univariate

¹⁵This is a common problem for both \widehat{lr}_t and \widehat{cay}_t , but is likely to be less severe for the former than the latter since their first autocorrelations are, respectively, .48 and .83.

regressions for both returns and excess returns. The R^2 ranges from 4 to 12 percent for $\hat{\varepsilon}_t$ and from 4 to 8 percent for $\hat{\varepsilon}_{t-1}$. The regressors are always strongly statistically significant and have the right sign implied by Table 1 and the estimated ARIMA process for labor income. The out-of-sample performance is also good, with a pseudo R^2 that ranges from 4 to 12 percent for $\hat{\varepsilon}_t$ and from 3 to 7 percent for $\hat{\varepsilon}_{t-1}$. When used jointly as regressors, the \bar{R}^2 are slightly higher than the ones obtained using \hat{lr}_t as the only regressor, but the pattern of both in-sample and out-of-sample performances are very similar to the ones of \hat{lr}_t in Table 1. When \widehat{cay}_t is introduced in the regression all the regressors are still strongly statistically significant and the in-sample and out-of-sample performance are almost the same, in term of \bar{R}^2 and pseudo R^2 , as the ones obtained in Table 1 using \hat{lr}_t and \widehat{cay}_t jointly as regressors.

A concern with the results on the empirical performance of \hat{lr}_t and \widehat{cay}_t as predictors of asset returns is the potential "look-ahead" bias, that might arise from the fact that the coefficients used to generate \hat{lr}_t and \widehat{cay}_t are estimated using the full data sample.¹⁶ To address this issue, Table 3 presents root mean square error and pseudo R^2 of out-of-sample one-step-ahead forecast computed estimating \hat{lr}_t using only *prior* data on labor income. The Table also report the *RMSE* for the benchmark case of constant return. Panel A, focuses on predicting real returns while Panel B hinges upon excess returns. The coefficients used to generate the regressor \hat{lr}_t are re-estimated each period using only data prior to the forecast period, and the predictive regressions are estimated recursively using data from the beginning of the sample to the quarter immediately preceding the forecast period. Beside being a robustness check of the previous results, this exercise is interesting per se since it reproduce the situation that a practitioner would face using \hat{lr}_t to forecast future asset returns.

Since Brennan and Xia (2002) show that changing the starting point of the out-of-sample forecast might dramatically change the measured performance, Table 3 uses three different starting point for the out-of-sample forecast. The first starting point

¹⁶For a discussion on the potential "look-ahead" bias in \widehat{cay}_t see Brennan and Xia (2002) and Lettau and Ludvigson (2002).

for the forecast period is, as in Table 1 and 2, the last quarter of 1962, allowing to first estimate each forecasting equation and the parameters of \widehat{lr}_t using the first ten years of available data. The other two starting points considered are the last quarters of 1972 and 1982, therefore adding ten and twenty years of data to the first estimations of the forecasting equations and of \widehat{lr}_t .

Focusing on the 1962:Q4 starting date, and comparing the results with the ones reported in Table 1 (that has the same starting date of out-of-sample forecast), it can be noticed that the pseudo R^2 measures of \widehat{lr}_t remain virtually unchanged (only one of them is reduced by one percent) and that there is very small increase in $RMSE$, suggesting that the results in Table 1 are not due to "look-ahead" bias.

The other two starting dates considered show a somehow smaller pseudo R^2 but the maximum reduction (that ranges from two to seven percent) is never as dramatic as in Brennan and Xia (2002).¹⁷ Moreover, the predictive power of \widehat{lr}_t is still remarkably high for the two quarters to one year ahead returns, with a pseudo R^2 between 8 and 11 percent, and a reduction in $RMSE$, with respect to the benchmark case of constant returns, between 3 and 6 percent.

Overall, the results obtained with \widehat{lr}_t as predictor of market returns seem to be robust and unlikely to be due to a spurious regression problem or a "look-ahead" bias.

The evidence on the predictive power of lr suggests that labor income risk is an important determinant of equilibrium market returns and that it is likely to be an important factor in households' optimal portfolio choice. The increase of forecasting power of \widehat{lr}_t with the horizon is also consistent with the theory behind equation (7), since it should track long-term tendencies in asset market rather than provide accurate short-term forecasts of crashes and booms. Moreover, the negative sign of this regressor in the forecasting equations in Table 1, as well as the negative signs of the

¹⁷Brennan and Xia (2002) perform a similar exercise using \widehat{cay}_t as predictor of asset return, and find that similar changes in the starting date of the forecast period delivers negative pseudo R^2 measures for this regressor. Lettau and Ludvigson (2002) reasonably argues that this finding is likely to be the consequence of a poor estimate of \widehat{cay}_t in shorter samples.

estimated coefficients for labor income innovations in table 2, have a clear economic interpretation. Positive labor income shocks increase the expected value of future labor income, in turn increasing lr . Therefore, an increase in lr represent a state of the world in which consumers are richer and expect their labor income to increase in the future. As a consequence, low returns on asset wealth are feared less. This in turn lead to lower equilibrium risk premia, lowering both equilibrium market returns and excess returns.

4 Forecasting consumption growth

In principle, equation (7) also implies that expected future labor income growth forecasts expectations of future consumption growth. In fact, there is little evidence of predictability of future consumption growth, reinforcing the conjecture that fluctuations in the labor income risk term (lr) should forecast asset returns.

Table 4 shows the results of forecasting consumption growth ($\log(C_{t+1+s}/C_{t+1})$) at different horizons (from $s = 1$ to $s = 12$ quarters). Estimation is performed using the left hand side variables of equation (7) as regressors both individually and jointly. The regressand in Panel A is total consumption¹⁸ growth, while Panel B employs nondurable consumption.

Focusing on total consumption, we observe that \widehat{lr}_t has some degree of forecasting ability, explaining 3 percent of the variation in consumption growth at one quarter horizon. The R^2 than rises up to 9 percent at one year horizon and than declines down to 3 percent at the four years horizon. The estimated slope coefficients are generally significant but small in magnitude: a one standard deviation change in \widehat{lr}_t implies

¹⁸The usual concern with using total consumption is that it contains expenditures on durable goods instead of the theoretically desired stock of durable goods. But expenditures and stocks are cointegrated, therefore long-term movement in expenditures also measures the long-term movement in consumption flows (see Ait-Sahalia, Parker, and Yogo (forthcoming)).

merely a 0.14% change in consumption growth over the next quarter and a 0.71% change over the next three years. Coherently with Lettau and Ludvigson (2001a), cay_t shows no forecasting ability for future consumption growth: its R^2 is very close to zero and the estimated slope coefficient is never statistically different from zero. When using the regressors jointly, the share of expected variation in consumption growth explained does not increase with respect to the univariate regressions with \widehat{lr}_t as the only explanatory variable, and the slope coefficients associated with this variable are basically unchanged.

When considering nondurable consumption (Panel B) the predictive power of \widehat{lr}_t is lower. To some extent this may be because consumption in equation (7) refers to total consumption flow.¹⁹ The share of variation in consumption growth explained by this regressor alone ranges from 1 to 6 percent. The regression coefficient is statistically not significant at one quarter and three year horizon and its size is economically small (a one standard deviation change in \widehat{lr}_t implies only an half a point percent change in nondurable consumption growth over the next three years). Even in this case \widehat{cay}_t shows no explanatory power and, as before, when the regressors are used jointly the results are basically unchanged from the univariate regressions with only \widehat{lr}_t as explanatory variable.

These results suggest that labor income risk has some degree of predictive ability for future consumption growth as implied by equation (7), and it performs better in predicting total consumption than the nondurable one. Nevertheless, the economic size of the long run effects of a change in lr_t on consumption growth is economically small. Returning to equation (7) and the results presented in section 3, this finding reinforce the conjecture that fluctuations in the labor income risk term (lr) should forecast asset returns.

¹⁹On the other hand, it is also the case that total consumption contains expenditures that should be correlated over time, especially with adjustment costs, and this could cause the higher degree of predictability of this series.

5 A skeptical look at the data: reduced form VAR approach

As a robustness check of the previous results, this section does not impose the theoretical restrictions implied by the budget constraint in equation (7), and shows that the joint estimation of the forecasting equations for labor income growth and market returns implies that labor income has a high marginal predictive power for returns. Moreover, both short and long run effects of labor income shocks on market returns are shown to be consistent with the findings presented in the previous sections.

In order to assess the predictive power of labor income growth for market returns, I fit a reduced Vector Autoregressive Model (VAR) for labor income, market returns and the other observable variables in the log-linearized budget constraint

$$X_t = A(L) X_{t-1} + \xi_t \quad (10)$$

where $X_t = [r_{a,t}, \Delta y_t, \Delta a_t, \Delta c_t]'$, $A(L)$ is a matrix that contains polynomials in the lag operator L and ξ_t is a vector of error terms.

This section focuses on the VAR specification in first differences in equation (10) with the selected optimal lag length of 2. Section C of the Appendix assesses the robustness of the findings by showing that *a*) the same results are obtained fitting a VAR in levels²⁰ (therefore allowing for cointegration among consumption, asset wealth and labor income) and *b*) the results are not sensible to the selected lag length.

Table 5 reports the measures of fit and the joint significance F -tests for the four sets of lagged regressors in the four forecasting equations of the VAR . The first column corresponds to the forecasting regression of market returns on past market returns, past labor income growth, past financial wealth growth and past consumption growth. The first thing to notice is that the degree of predictability of one quarter ahead market returns is in line with the results in Table 1. Moreover, the F -tests

²⁰Where $X_t = [r_{a,t}, y_t, a_t, c_t]'$

show that the predictive power of the regression is entirely due to past labor income growth rates, while the other regressors are far from being statistically significant (both individually and jointly). The second column corresponds to the forecasting equation for labor income growth. This variable appears to be highly predictable with a \bar{R}^2 of 45 percent. Past labor income growth rates are highly significant regressors, while past consumption growth and market returns are not significant and past asset wealth growth rates are significant only at the 5 percent level. Even in this case, most of the predictive power is ascribable to past labor income growth rates (constraining the coefficients on other regressors to be equal to zero, the measure of fit reduces by less than 3 percent). The last two columns correspond to the forecasting equations for asset wealth growth and consumption growth. Asset wealth growth appears to be very hard to predict while some degree of predictability is observed for consumption growth. Nevertheless, none of the regressors appear to be a statistically significant predictor in any of the two regressions.

With the estimated *VAR* model in hand, we can also assess the change in expected future returns caused by a shock to any of the forecasting variables considered. Figure 1 reports the response functions of quarterly market returns to a one standard deviation impulse in each of the regressors. The upper left panel shows that past market return shocks have no effect on future market returns. Similarly, the upper and lower right panels show that asset wealth and consumption shocks have no significant effect on expected future returns. Instead, the lower left panel shows that a labor income shocks causes a significant change in expected quarterly market returns over the first five quarters following the shock. Moreover, positive labor income shocks are associated with a reduction in expected returns, coherently with the log-linearized budget constraint and the findings reported in the previous sections using *lr* as forecasting variable.

Since the *VAR* confirms the qualitative results obtained using expected future labor income growth rates as predictor of future market returns, we can also ask whether the two approaches deliver quantitatively similar implications. Figure 2 addresses this

question. The solid line represents the cumulative effect of a one standard deviation negative labor income shock on market returns implied by the estimated *VAR*. The model predicts an economically significant role for labor income shocks, with a point estimate of the change in expected yearly returns of more than 4 percent. The dash-dotted line represents the effect of one standard deviation negative shock in expected labor income growth implied by the multivariate *OLS* regressions in Table 1 that uses *lr* as forecasting variable. It is clear from the graph that the effects of labor income shocks implied by the *VAR* closely match the results of the *OLS* regressions, and that the two are not statistically different.

Overall, the results obtained with the *VAR* approach confirm the soundness, both from a qualitative and quantitative point of view, of the findings reported in the previous sections.²¹

6 Explaining the cross-section of expected returns

This section explores *conditional* versions of the Consumption Capital Asset Pricing Model (CCAPM) where *lr* and its linear combination with *cay* are the conditioning variables. These models express the stochastic discount factor as a conditional (or *scaled*) factor model and are able to explain more than four fifth of the cross-sectional variation in average stock returns of the Fama and French (1992) 25 portfolios.

Explaining the cross-section of expected stock returns has been proven to be a hard task for most of the existing asset pricing models. The capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965) has virtually no power to explain the cross section of average returns on assets sorted by size and book-to-market ratios (Fama and French (1992, 1993), Lettau and Ludvigson (2001b)). The consumption CAPM (CCAPM), first developed by Rubinstein (1976) and Breeden (1979),

²¹Similar results are obtained with a *VAR* in levels (where $X_t = [r_{a,t}, y_t, a_t, c_t]'$) and are reported in the Appendix.

addressed the criticism of Merton (1973) (that the static CAPM failed to account for the intertemporal hedging component of asset demand) and Roll (1977) (that the market return cannot be proxied by an index of common stocks), but has been disappointing empirically, performing little better than the static CAPM in explaining the cross section of average asset returns (see Mankiw and Shapiro (1986), Breeden, Gibbons, and Litzenberger (1989), Campbell (1996), Cochrane (1996), Lettau and Ludvigson (2001b), Yogo (2003) and Parker and Julliard (2005)).

The results reported in section 3, and a large empirical literature,²² find that expected returns and excess returns on aggregate stock indexes are predictable, suggesting that risk premia are time-varying. The budget constraint in equation (7) suggests using $cay - (1 - v)lr$ as conditioning variable since it should capture expectations about future asset returns.

Moreover, the labor income risk term (lr) derived from the consumer's budget constraint is itself a natural candidate for capturing time varying risk in the economy. When lr is high and positive, consumers expect their labor income to increase in the future, with a consequent perceived reduction of the level of risk since, ceteris paribus, they will be less likely to have to reduce their future consumption because of a negative income shock.²³ Moreover, in the presence of liquidity constraints, a high lr represent a state of the world in which consumers are less likely to be constrained in the near future. This in turn should lead to lower equilibrium risk premia, lowering both equilibrium market returns and excess returns.

The stochastic discount factor (M_{t+1}) implied by the CCAPM is equal to the marginal rate of substitution between current and future consumption

$$M_{t+1} \equiv \delta \frac{U_c(C_{t+1}, Z_{t+1})}{U_c(C_t, Z_t)}$$

²²See, among others, Shiller (1984), Campbell and Shiller (1988), Fama and French (1988, 1989), Campbell (1991), Lamont (1998), Lettau and Ludvigson (2001a).

²³ lr increases when there are positive income shocks. Given the persistence in the income growth process, a positive labor income shock today has an insurance value since it will make a reduction of future labor income less likely.

where $U_c(\cdot)$ is the marginal utility of consumption, δ is the subjective rate of time preference and Z captures other factors that might influence utility. This can be generally approximated as

$$M_{t+1} \approx a_t + b_t \Delta \ln C_{t+1}$$

where a_t and b_t are potentially time-varying parameters.

Following Cochrane (1996), Ferson and Harvey (1999) and Lettau and Ludvigson (2001b), I model the variation in conditional moments by interacting ("scaling") the CCAPM factor with the conditioning variable.²⁴ This implies three factors models with factors given by: $cay_t - (1 - v)lr_t$, $\Delta \ln C_{t+1}$, and $[cay_t - (1 - v)lr_t] \times \Delta \ln C_{t+1}$ when $cay - (1 - v)lr$ is the conditioning variable; lr_t , $\Delta \ln C_{t+1}$ and $lr_t \Delta \ln C_{t+1}$ when lr is used as conditioning variable.

In what follows, the performance of these factor models in explaining the cross section of average stock returns is compared to the performance of the unconditional CCAPM and the factor models of Fama and French (FF) and Lettau and Ludvigson (LL).

Fama and French (1992, 1993) show that a three-factor model explains a large fraction of the cross-sectional variation in expected returns in the FF portfolios. The factors are the excess return on the market (denoted R^m), and the two excess returns capturing the value and size premia: the excess return on a portfolio containing stocks of firms with high ratios of book value to market equity relative to a portfolio of firms with low book value to market equity ("high minus low" denoted HML), and the excess return on a portfolio containing stocks of small firms relative to a portfolio of large firms ("small minus big" denoted SMB).

Lettau and Ludvigson (2001b) present a conditional CCAPM that uses cay as scaling variable. They show that \widehat{cay}_t , consumption growth ($\Delta \ln C_{t+1}$), and their interaction provide a three-factor model that does as well in explaining the cross-

²⁴This methodology builds on Ferson, Kandel, and Stambaugh (1987), Harvey (1989) and Shanken (1990) that suggest to scale the conditional betas themselves in linear cross-sectional regression model.

section of expected returns as the FF three-factor model.

Each of these models implies that the expected return on any portfolio is the weighted sum of the covariance of the return and each factor, and implies an unconditional multifactor beta representation of the form

$$E [R_{i,t+1}^e] = \beta' \lambda$$

where $R_{i,t+1}^e$ is the excess return on asset i , $\beta \equiv Cov(\mathbf{f}_{t+1}, \mathbf{f}'_{t+1})^{-1} Cov(\mathbf{f}_{t+1}, R_{i,t+1}^e)$, λ is a vector of coefficients that does not have a straightforward interpretation as risk price,²⁵ and \mathbf{f}_{t+1} is the vector of factors. We have $\mathbf{f}_{t+1} = \Delta \ln C_{t+1}$ in the unconditional CCAPM, $\mathbf{f}_{t+1} = (R_{t+1}^m, SMB_{t+1}, HML_{t+1})'$ in the FF model, $\mathbf{f}_{t+1} = (\widehat{cay}_t, \Delta \ln C_{t+1}, \widehat{cay}_t \Delta \ln C_{t+1})'$ in the LL model, and $\mathbf{f}_{t+1} = (\widehat{lr}_t, \Delta \ln C_{t+1}, \widehat{lr}_t \Delta \ln C_{t+1})'$ when lr_t is used as a conditioning variable for the CCAPM.

To test these models the analysis focuses on the quarterly returns on the Fama and French (1992) 25 portfolios and constructs excess returns as the returns on these portfolios minus the return on a three-month Treasury bill. These portfolios are of particular interest because they have a large dispersion in average returns that is relatively stable in sub-samples, and because they have been used extensively to evaluate asset pricing models. Moreover, they are designed to focus on two key features of average returns: the size effect – firms with small market value have on average higher returns – and the value premium – firms with high book values relative to market equity have on average higher returns.

More precisely, the FF 25 portfolios are the intersections of 5 portfolios formed on size (market equity, ME) and 5 portfolios formed on the ratio of book equity to market equity (B/M). Each portfolio is denoted by the rank of its ME and then the rank of its B/M , so that the portfolio 15 belongs to the smallest quintile of stocks by ME and the largest quintile of stocks by B/M . To match the frequency of consumption data, we convert returns to a quarterly frequency, so that $R_{i,t+1}^e$ represents the excess return on portfolio i during the quarter $t + 1$. The consumption time series is the

²⁵See Lettau and Ludvigson (2001b) for a discussion of this point.

(chain weighted) personal consumption expenditures on nondurable goods per capita from the National Income and Product Accounts.²⁶

Following Yogo (2003) and Parker and Julliard (2005), the models are estimated by Generalized Method of Moments (GMM) using the $(N + F) \times 1$ empirical moment function (where N is the number of portfolios considered and F is the number of factors)

$$g(\mathbf{R}_t^e, \mathbf{f}_t; \alpha, \mu, \mathbf{b}) = \begin{Bmatrix} \mathbf{R}_t^e - \alpha \mathbf{1}_{25} + \mathbf{R}_t^e (\mathbf{f}_t - \mu)' \mathbf{b} \\ \mathbf{f}_t - \mu \end{Bmatrix} \quad (11)$$

where \mathbf{R}_t^e is a vector containing the excess return on each asset considered, \mathbf{b} is a $F \times 1$ vector of coefficients on the factors and μ denotes a $F \times 1$ parameter vector. Under the null that the model prices expected returns, the theoretical moment restriction $E[g(\mathbf{R}_t^e, \mathbf{f}_t; \alpha, \mu, \mathbf{b})] = 0$ holds for the true $(\alpha, \mu', \mathbf{b}')$. The difference between the fitted first twenty five moment and zero is a measure of the misspricing of an expected return. The econometric specification includes an intercept (α) that allows all excess returns to be misspriced by a common amount.²⁷

Figure 3 plots the predicted and average returns of different portfolios for the four models considered using the FF25 value weighted portfolios. In each panel, the horizontal distance between a portfolio and the 45⁰ line is the extent to which the expected return based on the fitted model (on the horizontal axis) differs from the observed average return (on the vertical axis). All models, besides the unconditional CCAPM, do quite well at fitting expected returns. Both the FF model (in Panel B) and the LL model (Panel C), when compared to the unconditional CCAPM, reduce the pricing errors for 16 out of 25 portfolios considered. The conditional model with lr as scaling variable performs very well too, reducing the pricing errors of 18 out

²⁶Consumption and returns are allined using the standard “end of period” timing assumption that consumption during quarter t takes place at the end of the quarter. The alternative timing convention, used by Campbell (1999) for example, is that consumption occurs at the beginning of the period.

²⁷As a prespecified weighting matrix, the identity matrix is employed, resetting the diagonal entries for the moments $E[\mathbf{f}_t - \mu] = 0$ to very large numbers, as in Parker and Julliard (2005), so that the point estimates are identical to those from the Fama and MacBeth (1973) procedure.

of 25 portfolios when compared to the unconditional CCAPM. Moreover, it generally performs better than the other models in pricing the small firms. This is an important feature of the results given the well documented inability of linear factor models to price the small growth portfolio (i.e. the lowest quintile in both size and book-to-market equity, denoted 11 in Figure 3).²⁸ The failure in explaining the average return of portfolio 11 is generally justified invoking market frictions not considered by linear factor models and frictionless equilibrium models.²⁹ Our model instead prices this portfolio correctly, suggesting that the labor income risk factor is able to capture a features of the data normally unmatched by other models.

The fitted values in Figure 3 are based on the model estimate in Table 6, Panel A, with fixed weighting matrix. The first row of the panel refers to the unconditional CCAPM. The model performs poorly in several ways. First, contemporaneous consumption risk is not an economically significant determinant of the cross-section of expected returns. The first column displays the percent of the variation in average returns explained by the fitted model, given by the cross-sectional R^2 .³⁰ The consumption risk factor explains only 24 percent of the cross-sectional variation in average returns. Second, the estimated intercept (even though not statistically significant in the first stage estimate) implies that the average excess return on a FF portfolio exceeds that implied by the model by roughly 6 or 9 percent per year.³¹ Third, the model is rejected by the data both in the first and second stage (the seventh column presents the HJ distance and the p -value of a specification test based on this distance,

²⁸Yogo (2003), coherently with our estimation of FF and LL models, finds that the portfolio 11 is an outlier for all the models considered.

²⁹D’Avolio (2002) and Lamont and Thaler (2003) document limits to arbitrage, due to short-sale constraints, for the types of stocks that are generally characterized as small growth.

³⁰This measure of fit follows Jagannathan and Wang (1996) and is given by: $R^2 = 1 - \text{Var}_c \left(E_T [R_{i,t}^e] - \hat{R}_i^e \right) / \text{Var}_c (E_T [R_i^e])$ where $E_T[\cdot]$ is the time series average operator, Var_c denotes a cross-sectional variance, and \hat{R}_i^e is the fitted average return of asset i .

³¹This is consistent with the well-documented poor performance of the CCAPM in explaining the excess return on the market (Grossman and Shiller (1981) Hansen and Singleton (1982), Mehra and Prescott (1985)).

the last column reports the J -test and its p -value).

The second row refers to the FF factor model. The model explains a large part of the variation in average returns, delivering a cross-sectional R^2 of 73 percent. Moreover, the factors are jointly significant (even though not individually significant). Nevertheless the estimated intercept is very large and statistically significant, and the model is rejected in both GMM estimates.

The third row reports the performance of the LL model. This model delivers a good fit explaining 70 percent of the variation in average returns, but the factors jointly are not statistically significant (even though some of the factors are individually significant), the estimated α is large (even though not significant in the estimation with fixed weighting matrix) and the model is rejected in both GMM estimates. Moreover, there is a remarkable parameter instability between the two GMM estimates.

The fourth row of Panel A refers to the conditional CCAPM model with the labor income risk factor (lr) as scaling variable. The model explains four fifths of the variation in average returns (with a cross-sectional R^2 of 81 percent) and the factors are jointly significant. The estimated constant is still too large even though smaller (and statistically non significant) than the one implied by the FF and LL models, and the model is rejected by the data. This model too has a large parameter instability between the two estimates.

The fifth row is a conditional CCAPM that uses as scaling variable a linear combination of lr and cay , given by $cay - (1 - v)lr$ (with weight v to be determined by the GMM estimation), as equation (7) would suggest. Interestingly, this is the model that delivers the best fit (with a cross-sectional R^2 of 86 percent) and the lower HJ distance measure³² and implies that the expected return based on the fitted model is

³²The HJ distance would be the square root of a weighted average of the squared pricing errors if we did not include moments for the means of the factors. Since we do, this interpretation of the HJ distance as a measure of average pricing error is not strictly correct. However in this case this interpretation is not misleading given the small contribution to the measure deriving from the moments associated with the means of the factors.

off by (roughly) 0.57 percent per quarter for the “typical” portfolio. The estimated weight $1 - v$ has the right sign, is statistically different from zero and is not statistically different from the benchmark value of the of 2/3 for the human capital share of total wealth.³³ Nevertheless, the model is still rejected by the data, and shows some degree of parameter instability, but delivers the smaller J -test value.

Considering the results jointly it is clear that FF, LL and labor income risk model have comparable performance, with the last two models characterized by a larger parameters instability probably due to near-singularity of their optimal weighting matrices for the FF25 portfolios.

The remaining panels of Table 6 check for the robustness of the results obtained in Panel A for the first four models considered. Panel B focuses on the FF25 equally weighted portfolios. The results are qualitatively similar to the ones in Panel A with an increase in fit for all the models but the unconditional CCAPM. With this set of portfolios the labor income risk model performs particularly well, delivering a cross-sectional R^2 of 91 percent. This model, like the others, is still rejected by the data but has the lower HJ distance and J -test values among the models considered.

The last two panels of Table 6 consider two other different sets of portfolios.³⁴ Panel C looks at portfolios formed grouping assets according to their cash-flow price ratio deciles. In this case the unconditional CCAPM has no explanatory power delivering a cross-sectional R^2 of only 1 percent and is strongly rejected by the data. The FF model has a cross-sectional R^2 of 55 percent and a very small intercept, but the model is always rejected by the data. Both the LL and the labor income risk models perform well with a cross-sectional R^2 of 70 and 72 respectively. Moreover, these two models are not rejected by the data in both GMM estimates and the estimated coefficients are stable across estimates.

³³Moreover, imposing the restriction $1 - v = 2/3$ delivers results extremely similar to the ones reported.

³⁴All the portfolios data are taken from Kenneth French home page:
<http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/>

Very similar results for the labor income risk model are obtained using portfolios formed on dividend price ratio deciles and portfolios formed on earning price ratios deciles (not reported) , where this model is able to explain 68 and 80 percent, respectively, of the cross sectional variation in expected returns and is not rejected by the data.

LL and FF models also have similar good results with the earning price ratios portfolios (with a cross-sectional R^2 of 73 and 83 percent respectively). These last two models perform instead poorly in explaining the cross-section of portfolios formed on the dividend price ratios, delivering large and negative measures of fit.

Panel D focuses on the set of portfolios in which the labor income risk model performs worse among all the set of portfolios considered. This is a set of ten industry portfolios. In this case all the models considered performs poorly but the lr model still delivers the highest cross-sectional R^2 (24 percent, whit 13, -28 and -48 percent for the FF, LL and unconditional CCAPM models respectively) and an overall better performance than the other models considered.

Overall, the results obtained in this section seem to indicate that a conditional CCAPM with lr as conditioning variables performs as well as (or better than) the FF and LL factor models.

7 A structural interpretation

The success of lr in predicting future market returns, and its ability to explain the cross-section of asset returns when used as conditioning variable for the CCAPM, are compelling. What is the structural interpretation?

lr captures consumers expectations about their future labor income growth. Moreover, given the persistence of the labor income growth process, positive labor income shocks raise lr and the expected value of future labor income. In the presence of liquidity constraints for example, this also reduces the probability that the consumer will

be constrained in the future. Thus one possible interpretation of the results is that when lr is high consumers expect their labor income to grow in the future, therefore perceiving a lower level of risk since, *ceteris paribus*, they will be less likely to have to reduce future consumption due to a reduction in labor income. As a consequence, consumers will be willing to accept, in equilibrium, a lower level of risk premium on asset returns (this is also suggested by the sign of the coefficient associated with lr in the stock market predictability regressions of section 3 and the *VAR* exercise in section 5). If this were the case, we would expect to observe large upward swings in excess returns after lr registers large downward swing. Moreover, if lr was able to capture this kind of variation in risk premia, this would explain its success both as predictor of returns and as conditioning variable in the cross-sectional regressions presented.

Figure 4 plots the time series of \widehat{lr} and the stock market excess return (R^e).³⁵ The figure shows a multitude of episodes during which sharp increases in labor income risk (represented by a decrease in \widehat{lr}) precede large excess returns and decreases in labor income risk (represented by increases in \widehat{lr}) precede large reduction in the excess return. The labor income risk component also displays a clear business cycle pattern: \widehat{lr} decreases during recessions and increases during expansions. Only in two moments in time the relation between labor income risk and excess return seems to be weakened: the second oil shock period and the late 90's stock market boom and following crash³⁶ (but the relation seems to regain strength in the last observations of the sample).

The evidence presented in Figure 4 seems to support the view that the good performance of lr , both as predictor and conditioning variable, is due to its ability to capture time varying risk in the economy, therefore forecasting time varying risk premia.

³⁵Excess returns are constructed as the difference between the CRSP-VW market return index and the return on the three month Treasury bill. The time series are standardized to have unit variance and smoothed to facilitate the reading.

³⁶If we had to take the argument about the link between lr and R^e presented here literally, Figure 4 would be indicating a bubble in the stock market in the late 90's.

This interpretation leaves the open question of which kind of asset pricing model could rationalize these findings. Bansal and Yaron (2004) model consumption and dividend growth as containing a small predictable component and show, with a calibration exercise, that a Kreps-Porteus-Epstein-Zin-Weil³⁷ preference setting can explain some key asset market phenomena.

Building on their approach, and assuming that the predictable component of consumption and dividend growth is the same predictable component of labor income growth, it is possible to show that past labor income innovations will predict asset returns consistently with the good empirical performance of lr both as predictor and conditioning variable. The model is characterized by the utility function

$$U_t = \left\{ (1 - \delta) C_t^{\frac{1-\gamma}{\theta}} + \delta (E_t [U_{t+1}^{1-\gamma}])^{\frac{1}{\theta}} \right\}^{\frac{\theta}{1-\gamma}}$$

where $\theta := (1 - \gamma) / (1 - \psi^{-1})$, and γ and ψ are, respectively, the relative risk aversion and intertemporal elasticity of substitution coefficients, $0 < \delta < 1$ is the time discount factor, and the budget constraint is given by equation (3). When $\theta = 1$ this reduces to the standard CRRA setting. The implied Euler equation is

$$1 = E_t \left[\delta^\theta \left(\frac{C_{t+1}}{C_t} \right)^{-\frac{\theta}{\psi}} (1 + R_{w,t+1})^{-(1-\theta)} (1 + R_{i,t+1}) \right].$$

Following Bansal and Yaron (2004), let the log dividend and log consumption growth rates follow the processes

$$\Delta c_{t+1} = \mu_c + \phi_c x_t + \sigma_c \eta_{t+1}$$

$$\Delta d_{t+1} = \mu_d + \phi_d x_t + \sigma_d u_{t+1}$$

where $\eta_{t+1}, u_{t+1} \sim i.i.d.N(0, 1)$. Assume also that the log labor income follows the ARIMA(0,1,2) process

$$\begin{aligned} \Delta y_{t+1} &= \mu_y + \varepsilon_{t+1} + x_t \\ &= \mu_y + \varepsilon_{t+1} + \vartheta_1 \varepsilon_t + \vartheta_2 \varepsilon_{t-1} \end{aligned}$$

³⁷Epstein and Zin (1989, 1991) and Weil (1989) build on the approach of Kreps and Porteus (1978).

where $\varepsilon_t = \sigma_y \epsilon_t$ and $\epsilon_t \sim i.i.d.N(0, 1)$. This specification of the labor income process is the one employed in constructing lr , but here I introduce the additional assumption that the predictable component x_t is common to all the stochastic processes considered.

In this setting the conditional expectation of log market returns will depend on past labor income innovations³⁸

$$E_t[r_{a,t+1}] = \bar{r} - \left(\phi_d - \frac{\theta}{\psi} \frac{\phi_c}{[(\theta - 1)v + 1]} \right) (\vartheta_1 \varepsilon_t + \vartheta_2 \varepsilon_{t-1}).$$

Note that, if the predictable component of consumption is sufficiently small and $\phi_d > 0$, the correlation between past labor income innovations and future asset returns will be negative coherently with the results in Table 2. Similarly, the conditional risk premia will be time varying and predictable using past labor income innovations since

$$E_t[r_{a,t+1}] - r_{f,t+1} = B_0 + B_1 \varepsilon_t + B_2 \varepsilon_{t-1}$$

where

$$B_1 = - \left(\phi_d + \frac{\theta}{\psi} \frac{(\theta - 1)v}{(\theta - 1)v + 1} \phi_c \right) \vartheta_1 + (\theta - 1)v \left(\phi_d - \frac{\theta}{\psi} \frac{\phi_c}{[(\theta - 1)v + 1]} \right) \vartheta_2$$

$$B_2 = - \left(\phi_d + \frac{\theta}{\psi} \frac{(\theta - 1)v}{(\theta - 1)v + 1} \phi_c \right) \vartheta_2,$$

implying that, with a small degree of predictability of consumption growth, $\phi_d > 0$ and $\theta < 1$,³⁹ risk premia will be negatively correlated with labor income innovations as shown in Table 2 and Figure 4. Moreover, since past labor income innovations will capture variations in conditional risk premia, this finding is coherent with the good performance of lr as conditioning variable in explaining the cross-section of asset returns.

³⁸Details of the derivations are reported in section D of the Appendix.

³⁹Bansal and Yaron (2004) need a value of $\theta < 0$ to match the equity premium observed in the data.

8 Conclusion

This paper uses the representative consumer's budget constraint to derive an equilibrium relation between expected future labor income growth rates (summarized by the variable lr) and expected future asset returns, and explores whether the empirical counterpart of these expected changes in labor income (\widehat{lr}) carries relevant information to predict future asset returns and explain the cross-section of average asset returns.

The main finding of the paper is that \widehat{lr} has high predictive power for future market returns and, when used as conditioning variable for the Consumption Capital Asset Pricing model (CCAPM), delivers a linear factor model that rivals the Fama and French (1993) three-factor model and the Lettau and Ludvigson (2001b) three-factor model in explaining the cross-section of expected returns of the Fama and French size and book-to-market portfolios. Moreover, the conditional factor model proposed prices correctly the small growth portfolio and performs well in explaining the cross-section of expected returns for a wide range of portfolio data sets.

The success of lr as predictor of asset returns and conditioning variable is due to its ability to track time varying equilibrium risk premia: expectations of high future labor income are associated with lower stock market excess returns, while low labor income growth expectation are associated with higher than average excess returns. I interpret this as being due to the fact that high lr represent a state of the world in which agents expect to have abundance of resources in the future to finance consumption, therefore low returns on asset wealth are feared less and lower equilibrium risk premia are required. The paper also shows that these findings are consistent with a Kreps-Porteus-Epstein-Zin-Weil preferences framework where consumption growth, dividend growth and labor income growth share a small predictable component.

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Appendix

A Data description

All the data used in the paper are available over the sample period 1952:04 to 2001:4. The proxy chosen for the market return is the value weighted CRSP (CRSP-VW) market return index. The CRSP index includes NYSE, AMEX and NASDAQ, and should provide a better proxy for market returns than the Standard & Poor (S&P) index since it is a much broader measure.⁴⁰ The proxy for the risk free rate is the return on the 30-day Treasury bill. Labor income data are taken from the BEA National Income and Product table 1.14 available through DRI. The time series of \widehat{cay}_t is taken from Sidney Ludvigson's homepage.⁴¹ Population data are three-month averages of monthly data from the U.S. Census data available through DRI.

All the portfolios data are taken from Kenneth French home page.⁴² The FF 25 portfolios are the intersections of 5 portfolios formed on size (market equity, ME) and 5 portfolios formed on the ratio of book equity to market equity (B/M). Each portfolio is denoted by the rank of its ME and then the rank of its B/M , so that the portfolio 15 belongs to the smallest quintile of stocks by ME and the largest quintile of stocks by B/M . To match the frequency of labor income and consumption data, I convert returns to a quarterly frequency, so that $R_{i,t+1}^e$ represents the excess return on portfolio i during the quarter $t + 1$. Portfolios formed on cash-flow price ratios, dividend price ratios and earning price ratios are formed grouping assets according to the decile they belong to. The ten industry portfolios are constructed assigning each NYSE, AMEX, and NASDAQ stock to an industry portfolio at the end of June of year τ based on its four-digit SIC code at that time. Returns from July of τ to June of $\tau + 1$ are then computed.

⁴⁰Results analogous to the ones reported in the paper have been obtained using the S&P index.

⁴¹<http://www.econ.nyu.edu/user/ludvigsons>

⁴²<http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/>

The consumption time series is the (chain weighted) personal consumption expenditures on nondurable goods per capita from the National Income and Product Accounts. Consumption and returns are aligned using the standard “end of period” timing assumption that consumption during quarter t takes place at the end of the quarter.⁴³ The inflation series is constructed using the consumption price deflator.

B Estimation of the labor income risk factor

In order to model the labor income process, we experimented with several specification in the ARIMA class, and performed the standard set of Box-Jenkins selection procedures. In particular, among the model considered, MA(2) and ARMA(1,1) process fit well to first differences of log labor income. These specifications deliver similar results in term of predictability of asset returns and fit of the cross-section of asset returns, we henceforth restrict attention to the ARIMA(0,1,2) specification for log income since it simplifies the exposition and it has previously used in the literature in similar contexts.⁴⁴ Thus, the fitted earning specification is

$$\Delta y_t = \mu_y + \varepsilon_t + \vartheta_1 \varepsilon_{t-1} + \vartheta_2 \varepsilon_{t-2} \quad (\text{B.1})$$

where ε_t is the time t earning innovation and the ϑ 's are moving-average coefficients. Estimated coefficients are reported in Table A1.

Table A1: Estimated Labor Income Process

$\widehat{\mu}_y$	$\widehat{\vartheta}_1$	$\widehat{\vartheta}_2$	st. error of $\widehat{\varepsilon}$
0.013	1.531	0.598	0.0045
(0.0008)	(0.0552)	(0.0558)	

Note: Newey-West standard errors reported in brackets

The empirical counterpart of $lr_t = E_t \sum_{i=1}^{\infty} \rho_h^{i-1} \Delta y_{t+i}$ is therefore computed, disregarding the constant part, as

$$\widehat{lr}_t = \left(\widehat{\vartheta}_1 + \rho_h \widehat{\vartheta}_2 \right) \widehat{\varepsilon}_t + \widehat{\vartheta}_2 \widehat{\varepsilon}_{t-1}$$

⁴³The alternative timing convention, used by Campbell (1999) for example, is that consumption occurs at the beginning of the period.

⁴⁴See Davis and Willen (2000) and MaCurdy (1982).

where the $\hat{\varepsilon}$'s are the estimated innovations of equation (B.1) and ρ_h is calibrated, as in Baxter and Jermann (1997), at the value $\rho^h = 0.955$.

C Alternative VAR specifications

This section checks the robustness of the results reported in section 5 by considering different lag lengths and estimating a VAR in levels where $X_t = [r_{a,t}, y_t, a_t, c_t]'$.

Table A2 reports the measures of fit and the joint significance F -tests for the four sets of lagged regressors in the market return forecasting equation of several VAR specifications. The right panel focuses on the VAR in first differences and the left panel on VAR in levels, therefore allowing for the cointegration of consumption, asset wealth and labor income as the budget constraint suggests. Both panels consider lag lengths from 1 to 4. Overall, the VAR in levels seem to fit better than the VAR in first differences. In all the specifications considered, as in Table 5, the predictive power of the regressions is almost entirely ascribable to lagged labor income: past labor income, both in levels and in first differences, is always statistically significant while the other regressors are never significantly different from zero except asset wealth (at the 5 percent level) in the VAR in levels with four lags.

The impulse-response functions of market return, and the cumulative effect of a labor income shock on market returns implied by the VAR in levels are substantially in line with the ones obtained with VAR in first differences. Figure A1 reports the impulse-response functions of quarterly market returns to a one standard deviation shock in labor income (in the upper panel) and its cumulative effect (in the lower panel) implied by the VAR in levels with 3 lags. The effects of the labor income shocks are extremely similar to the ones in Figure 1 and Figure 2, but the cumulative effect is slightly smaller (even though the difference is not statistically significant). This seem to be caused by a bias toward stationarity in the estimation of the VAR in levels, and the difference disappears introducing a unit root prior for consumption, asset wealth and labor income.

D Epstein-Zin preferences

Epstein and Zin (1989, 1991) and Weil (1989) build on the approach of Kreps and Porteus (1978). The model is characterized by the utility function

$$U_t = \left\{ (1 - \delta) C_t^{\frac{1-\gamma}{\theta}} + \delta (E_t [U_{t+1}^{1-\gamma}])^{\frac{1}{\theta}} \right\}^{\frac{\theta}{1-\gamma}}$$

where $\theta := (1 - \gamma) / (1 - \psi^{-1})$, γ and ψ are, respectively, the RRA and IES coefficients, $0 < \delta < 1$ is the time discount factor, and the budget constraint is given by equation (3). When $\theta = 1$ this reduces to the standard CRRA setting.

The implied Euler equation is

$$1 = E_t \left[\delta^\theta \left(\frac{C_{t+1}}{C_t} \right)^{-\frac{\theta}{\psi}} (1 + R_{w,t+1})^{-(1-\theta)} (1 + R_{i,t+1}) \right]$$

and the log stochastic discount factor is given by

$$m_{t+1} = \theta \log \delta - \frac{\theta}{\psi} \Delta c_{t+1} + (\theta - 1) r_{w,t+1}.$$

Following Campbell (1996), Campbell and Shiller (1988) and Shiller (1993) we can approximate

$$\begin{aligned} r_{w,t} &\approx r + v r_{a,t} + (1 - v) (E_t - E_{t-1}) \sum_{j=0}^{\infty} \rho_h^j \Delta y_{t+j} \\ &= v r_{a,t} + (1 - v) [\Delta y_t + \rho_h l r_t - l r_{t-1}]. \end{aligned}$$

Therefore, the log stochastic discount factor

$$m_{t+1} \approx \bar{k} - \frac{\theta}{\psi} \Delta c_{t+1} + (\theta - 1) v r_{a,t+1} + (1 - v) (\theta - 1) [\Delta y_{t+1} + \rho_h l r_{t+1} - l r_t]$$

depends on the labor income risk factor lr . Moreover, in this set up, we can show that expected returns will depend on the labor income innovations.

Assume that the log labor income follows the ARIMA(0,1,2) process

$$\begin{aligned} \Delta y_{t+1} &= \mu_y + \varepsilon_{t+1} + x_t \\ &= \mu_y + \varepsilon_{t+1} + \vartheta_1 \varepsilon_t + \vartheta_2 \varepsilon_{t-1}. \end{aligned}$$

where $\varepsilon_t \sim i.i.d.N(0, \sigma_y^2)$. This implies that

$$m_{t+1} = \bar{k} - \frac{\theta}{\psi} \Delta c_{t+1} + (\theta - 1) v r_{a,t+1} + \lambda_1 \varepsilon_{t+1}$$

where $\lambda_1 = (1 - v)(\theta - 1)[1 + \rho_h(\vartheta_1 + \rho_h \vartheta_2)]$.

Following Bansal and Yaron (2004), let the log dividend and log consumption growth rates follow the processes

$$\Delta c_{t+1} = \mu_c + \phi_c x_t + \sigma_c \eta_{t+1}$$

$$\Delta d_{t+1} = \mu_d + \phi_d x_t + \sigma_d u_{t+1}$$

where $\eta_{t+1}, u_{t+1} \sim i.i.d.N(0, 1)$.

Note that we can approximate the log return on the market portfolio around the steady state price dividend ratio as

$$\begin{aligned} r_{a,t+1} &= \log \left(\left(\frac{P_{t+1}}{D_{t+1}} + 1 \right) \frac{D_{t+1}}{D_t} \frac{D_t}{P_t} \right) \\ &= k_0 + k_1 z_{a,t+1} + \Delta d_{t+1} - z_{a,t} \end{aligned}$$

where $z_{a,t+1}$ is the log price-dividend ratio ($\log \frac{P_{t+1}}{D_{t+1}}$) and $k_1 = \frac{P/D}{P/D+1}$.

From the Euler equation we have that

$$1 = E_t [\exp(m_{t+1} + r_{a,t+1})],$$

implying a first order difference equation for $z_{a,t}$

$$\exp \lambda_0 z_{a,t} = E_t \left[\exp \left(\begin{aligned} &\left[\bar{k} - \frac{\theta}{\psi} \mu_c + \lambda_0 k_0 + \lambda_0 \mu_d \right] - \frac{\theta}{\psi} \sigma_c \eta_{t+1} + \lambda_0 \sigma_d u_{t+1} \\ &+ \left(\lambda_0 \phi_d - \frac{\theta}{\psi} \phi_c \right) (\vartheta_1 \varepsilon_t + \vartheta_2 \varepsilon_{t-1}) + \lambda_0 k_1 z_{a,t+1} + \lambda_1 \varepsilon_{t+1} \end{aligned} \right) \right]$$

where $\lambda_0 = [(\theta - 1)v + 1]$. Guessing the solution to be of the form

$$z_{a,t+1} = A_0 + A_1 \varepsilon_{t+1} + A_2 \varepsilon_t$$

and matching the coefficients we have that

$$\begin{aligned} A_1 &= \left(\phi_d - \frac{\theta}{\psi} \frac{\phi_c}{[(\theta - 1)v + 1]} \right) (k_1 \vartheta_2 + \vartheta_1) \\ A_2 &= \left(\phi_d - \frac{\theta}{\psi} \frac{\phi_c}{[(\theta - 1)v + 1]} \right) \vartheta_2. \end{aligned}$$

The return on the market portfolio will be

$$r_{a,t+1} = k_0 + A_0 (k_1 - 1) + \mu_d + \sigma_d \eta_{t+1} + k_1 A_1 \varepsilon_{t+1} + \\ - \left(\phi_d - \frac{\theta}{\psi} \frac{\phi_c}{[(\theta - 1)v + 1]} \right) (\vartheta_1 \varepsilon_t + \vartheta_2 \varepsilon_{t-1}),$$

and will have the conditional expectation

$$E_t [r_{a,t+1}] = k_0 + A_0 (k_1 - 1) + \mu_d - \left(\phi_d - \frac{\theta}{\psi} \frac{\phi_c}{[(\theta - 1)v + 1]} \right) (\vartheta_1 \varepsilon_t + \vartheta_2 \varepsilon_{t-1}).$$

From the Euler equation we can also solve for the risk free rate obtaining

$$r_{f,t+1} = -\bar{k} + \frac{\theta}{\psi} \mu_c - (\lambda_0 - 1) A_0 - \frac{1}{2} \left\{ [(\lambda_0 - 1) A_1 + \lambda_1]^2 \sigma_y^2 + \left(\frac{\theta \sigma_c}{\psi} \right)^2 \right\} \\ - \left((\lambda_0 - 1) A_2 - \frac{\theta}{\psi} \phi_c \vartheta_1 \right) \varepsilon_t + \frac{\theta}{\psi} \phi_c \vartheta_2 \varepsilon_{t-1}.$$

Implying the conditional risk premia

$$E_t [r_{a,t+1}] - r_{f,t+1} = B_0 + B_1 \varepsilon_t + B_2 \varepsilon_{t-1}$$

where

$$B_0 = k_0 + A_0 (k_1 - 1) + \mu + \bar{k} - \frac{\theta}{\psi} \mu_c + (\lambda_0 - 1) A_0 \\ + \frac{1}{2} \left\{ [(\lambda_0 - 1) A_1 + \lambda_1]^2 \sigma_y^2 + \left(\frac{\theta \sigma_c}{\psi} \right)^2 \right\} \\ B_1 = - \left(\phi_d + \frac{\theta}{\psi} \frac{(\theta - 1)v}{(\theta - 1)v + 1} \phi_c \right) \vartheta_1 + (\theta - 1)v \left(\phi_d - \frac{\theta}{\psi} \frac{\phi_c}{[(\theta - 1)v + 1]} \right) \vartheta_2 \\ B_2 = - \left(\phi_d + \frac{\theta}{\psi} \frac{(\theta - 1)v}{(\theta - 1)v + 1} \phi_c \right) \vartheta_2$$

Therefore, past labor income innovations will predict future asset returns as found in the empirical analysis presented. Moreover, for a low degree of predictability of consumption growth (small ϕ_c) the correlation between labor income innovations and future market returns will be negative (given the estimated MA coefficients of labor income growth) coherently with the empirical results of the previous sections.

Table 1: Forecasting Stock Returns

		<i>Panel A: Real Returns</i>															
Dependent variable:		$r_{t,t+1}$				$r_{t,t+2}$				$r_{t,t+3}$				$r_{t,t+4}$			
Independent variable(s):	R^2	0.01	0.05	0.08	0.11	0.00	0.09	0.15	0.19	0.00	0.13	0.20	0.26	0.00	0.16	0.26	0.33
	\overline{R}^2	0.00	0.05	0.08	0.10	0.00	0.08	0.15	0.18	-0.01	0.12	0.20	0.25	-0.01	0.16	0.25	0.32
	$r_{t-1,t}$	0.09				0.03				0.02				0.00			
		(0.07)				(0.12)				0.00				(0.16)			
	lr_t		-2.20		-1.53		-4.18		-2.84		-6.10		-4.20		-7.98		-5.54
			(0.54)		(0.51)		(0.88)		(0.89)		(1.23)		(1.16)		(1.50)		(1.28)
	cay_t			1.95	1.63			3.84	3.25			5.48	4.60			7.07	5.92
			(0.53)	(0.52)			(1.01)	(1.02)			(1.41)	(1.39)			(1.75)	(1.69)	
	$RMSE$	0.0855	0.0834	0.0823	0.0813	0.1244	0.1190	0.1160	0.1137	0.1503	0.1416	0.1370	0.1332	0.1737	0.1602	0.1513	0.1454
	Pseudo R^2	0.00	0.05	0.08	0.10	0.00	0.08	0.13	0.16	0.00	0.11	0.17	0.21	0.00	0.15	0.24	0.30
		<i>Panel B: Excess Returns</i>															
Dependent variable:		$r_{t,t+1}^e$				$r_{t,t+2}^e$				$r_{t,t+3}^e$				$r_{t,t+4}^e$			
Independent variable(s):	R^2	0.00	0.05	0.07	0.10	0.00	0.09	0.13	0.17	0.00	0.13	0.18	0.24	0.00	0.17	0.23	0.31
	\overline{R}^2	0.00	0.05	0.07	0.09	-0.01	0.08	0.13	0.16	-0.01	0.12	0.17	0.23	0.00	0.16	0.22	0.30
	$r_{t-1,t}^e$	0.07				0.00				-0.02				-0.06			
		(0.07)				(0.15)				(0.15)				(0.14)			
	lr_t		-2.13		-1.51		-4.05		-2.84		-5.98		-4.28		-7.77		-5.61
			(0.51)		(0.51)		(0.85)		(0.91)		(1.23)		(1.24)		(1.46)		(1.35)
	cay_t			1.81	1.50			3.53	2.94			4.99	4.10			6.41	5.25
			(0.49)	(0.49)			(0.91)	(0.93)			(1.25)	(1.24)			(1.50)	(1.45)	
	$RMSE$	0.0844	0.0826	0.0816	0.0808	0.1214	0.1168	0.1146	0.1126	0.1446	0.1367	0.1340	0.1303	0.1653	0.1530	0.1470	0.1413
	Pseudo R^2	0.00	0.04	0.07	0.08	0.00	0.07	0.11	0.14	0.00	0.11	0.14	0.19	0.00	0.15	0.21	0.27

Newey-West corrected standard errors in brackets under the estimated coefficients.

Table 2: Forecasting Stock Returns Using Labor Income Innovations

		<i>Panel A: Real Returns</i>															
Dependent variable:		$r_{t,t+1}$				$r_{t,t+2}$				$r_{t,t+3}$				$r_{t,t+4}$			
Independent variable(s):	R^2	0.04	0.04	0.07	0.12	0.06	0.07	0.12	0.20	0.08	0.10	0.17	0.28	0.12	0.08	0.19	0.34
	\overline{R}^2	0.03	0.03	0.06	0.10	0.05	0.06	0.11	0.19	0.08	0.10	0.16	0.27	0.12	0.08	0.18	0.33
	ε_t	-3.99		-3.71	-2.64	-7.58		-7.05	-4.90	-10.96		-10.16	-7.14	-15.24		-14.42	-10.41
		(1.21)		(1.19)	(1.08)	(1.84)		(1.68)	(1.65)	(2.58)		(2.28)	(2.17)	(2.99)		(2.61)	(2.32)
	ε_{t-1}		-4.22	-3.95	-2.86		-8.07	-7.57	-5.38		-12.11	-11.39	-8.31		-12.63	-11.60	-7.51
			(1.27)	(1.30)	(1.37)		(1.98)	(1.94)	(1.84)		(2.67)	(2.57)	(2.06)		(3.35)	(3.20)	(2.36)
	cay_t				1.53				3.05				4.29				5.69
				(0.56)				(1.04)				(1.37)				(1.65)	
	$RMSE$	0.0841	0.0843	0.0829	0.0810	0.1204	0.1221	0.1185	0.1133	0.1442	0.1452	0.1397	0.1316	0.1632	0.1689	0.1591	0.1446
	Pseudo R^2	0.04	0.03	0.06	0.11	0.06	0.04	0.09	0.17	0.08	0.07	0.13	0.23	0.12	0.05	0.16	0.31
		<i>Panel B: Excess Returns</i>															
Dependent variable:		$r_{t,t+1}^e$				$r_{t,t+2}^e$				$r_{t,t+3}^e$				$r_{t,t+4}^e$			
Independent variable(s):	R^2	0.03	0.04	0.07	0.11	0.06	0.07	0.12	0.19	0.08	0.10	0.17	0.26	0.12	0.08	0.19	0.31
	\overline{R}^2	0.03	0.03	0.06	0.09	0.05	0.06	0.11	0.17	0.08	0.10	0.16	0.25	0.12	0.08	0.18	0.30
	ε_t	-3.87		-3.61	-2.62	-7.29		-6.76	-4.84	-10.74		-9.96	-7.29	-14.91		-14.13	-10.59
		(1.18)		(1.15)	(1.07)	(1.80)		(1.61)	(1.67)	(2.61)		(2.29)	(2.32)	(2.95)		(2.55)	(2.47)
	ε_{t-1}		-4.07	-3.81	-2.81		-7.98	-7.50	-5.54		-11.85	-11.14	-8.42		-12.07	-11.07	-7.46
			(1.23)	(1.26)	(1.36)		(2.01)	(1.96)	(1.93)		(2.66)	(2.55)	(2.16)		(3.25)	(3.07)	(2.45)
	cay_t				1.39				2.73				3.78				5.02
				(0.53)				(0.95)				(1.22)				(1.43)	
	$RMSE$	0.0831	0.0833	0.0821	0.0805	0.1179	0.1194	0.1163	0.1121	0.1390	0.1402	0.1351	0.1289	0.1555	0.1615	0.1522	0.1408
	Pseudo R^2	0.03	0.03	0.05	0.09	0.06	0.03	0.08	0.15	0.08	0.06	0.13	0.21	0.12	0.05	0.15	0.28

Newey-West corrected standard errors in brackets under the estimated coefficients.

Table 3: Pseudo R^2 and Root Mean Square Errors of Out-of-Sample Forecasts of Market Returns with Re-Estimated lr

<i>Panel A: Real Returns</i>												
	$r_{t,t+1}$			$r_{t,t+2}$			$r_{t,t+3}$			$r_{t,t+4}$		
First forecast period	constant	lr_t		constant	lr_t		constant	lr_t		constant	lr_t	
	<i>RMSE</i>	<i>RMSE</i>	Pseudo R^2	<i>RMSE</i>	<i>RMSE</i>	Pseudo R^2	<i>RMSE</i>	<i>RMSE</i>	Pseudo R^2	<i>RMSE</i>	<i>RMSE</i>	Pseudo R^2
1962:Q4	0.0861	0.0844	0.04	0.1252	0.1203	0.08	0.1515	0.1432	0.11	0.1756	0.1623	0.15
1972:Q4	0.0905	0.0895	0.02	0.1316	0.1277	0.06	0.1590	0.1527	0.08	0.1843	0.1737	0.11
1982:Q4	0.0811	0.0804	0.02	0.1098	0.1067	0.05	0.1288	0.1232	0.09	0.1477	0.1419	0.08

<i>Panel B: Excess Returns</i>												
	$r_{t,t+1}^e$			$r_{t,t+2}^e$			$r_{t,t+3}^e$			$r_{t,t+4}^e$		
First forecast period	constant	lr_t		constant	lr_t		constant	lr_t		constant	lr_t	
	<i>RMSE</i>	<i>RMSE</i>	Pseudo R^2	<i>RMSE</i>	<i>RMSE</i>	Pseudo R^2	<i>RMSE</i>	<i>RMSE</i>	Pseudo R^2	<i>RMSE</i>	<i>RMSE</i>	Pseudo R^2
1962:Q4	0.0850	0.0834	0.04	0.1223	0.1179	0.07	0.1462	0.1382	0.11	0.1678	0.1549	0.15
1972:Q4	0.0891	0.0883	0.02	0.1279	0.1246	0.05	0.1519	0.1462	0.07	0.1740	0.1642	0.11
1982:Q4	0.0800	0.0794	0.02	0.1079	0.1049	0.05	0.1262	0.1203	0.09	0.1441	0.1376	0.09

Table 4: Forecasting Consumption Growth

<i>Horizon (quarters)</i>	<i>Panel A: Total Consumption</i>					<i>Panel B: Nondurable Consumption</i>				
	R^2	\bar{R}^2	lr_t	cay_t	$\chi^2(2)^*$	R^2	\bar{R}^2	lr_t	cay_t	$\chi^2(2)^*$
1	0.03	0.02	-0.14			0.01	0.00	-0.07		
			(0.06)	0.003				(0.05)	0.02	
	0.00	-0.01		(0.07)		0.00	0.00		(0.07)	
2	0.03	0.02	-0.15	-0.03	5.46	0.01	0.00	-0.07	0.01	1.67
			(0.07)	(0.07)	(0.065)			(0.06)	(0.07)	(0.434)
	0.06	0.05	-0.33			0.03	0.02	-0.21		
4			(0.11)	0.03				(0.08)	0.03	
	0.00	0.00		(0.15)		0.00	0.00		(0.14)	
	0.06	0.05	-0.35	-0.04	9.35	0.03	0.02	-0.22	-0.01	7.44
6			(0.11)	(0.15)	(0.009)			(0.08)	(0.14)	(0.024)
	0.09	0.08	-0.66			0.06	0.05	-0.48		
			(0.19)	0.08				(0.15)	0.05	
8	0.00	0.00		(0.28)		0.00	0.00		(0.28)	
	0.09	0.08	-0.68	-0.06	13.09	0.06	0.05	-0.50	-0.05	14.02
			(0.20)	(0.28)	(0.001)			(0.13)	(0.27)	(0.001)
12	0.08	0.07	-0.82			0.06	0.05	-0.61		
			(0.25)	0.11				(0.21)	0.11	
	0.00	0.00		(0.34)		0.00	0.00		(0.34)	
4	0.08	0.07	-0.84	-0.06	11.27	0.06	0.05	-0.61	-0.02	9.77
			(0.26)	(0.35)	(0.004)			(0.20)	(0.33)	(0.008)
	0.05	0.05	-0.77			0.03	0.03	-0.53		
8			(0.31)	0.12				(0.25)	0.13	
	0.00	0.00		(0.36)		0.00	0.00		(0.35)	
	0.05	0.04	-0.79	-0.04	6.12	0.03	0.02	-0.52	0.02	4.54
12			(0.34)	(0.37)	(0.047)			(0.25)	(0.35)	(0.103)
	0.03	0.02	-0.71			0.02	0.01	-0.48		
			(0.48)	0.06				(0.35)	0.14	
12	0.00	-0.01		(0.34)		0.00	0.00		(0.32)	
	0.03	0.02	-0.74	-0.09	2.27	0.02	0.01	-0.46	0.04	1.95
			(0.52)	(0.37)	(0.321)			(0.37)	(0.34)	(0.376)

Newey-West corrected standard errors in brackets under the estimated coefficients.

* p -values in brackets under the test of joint significance of the regressors.

Table 5: F -tests and Measures of Fit of the VAR Estimation

Dependent variables:	r	Δy	Δa	Δc	
R^2	0.08	0.47	0.03	0.15	
\overline{R}^2	0.04	0.45	-0.01	0.11	
Independent variables:	r	0.82	2.83	0.91	1.86
		[0.441]	[0.061]	[0.403]	[0.158]
	Δy	5.31	44.27	1.59	1.39
		[0.006]	[0.000]	[0.207]	[0.252]
	Δa	0.48	3.84	0.57	0.39
		[0.620]	[0.023]	[0.565]	[0.675]
	Δc	0.74	1.51	0.90	1.31
		[0.479]	[0.222]	[0.409]	[0.273]

Significance levels in brackets under the F -statistics.

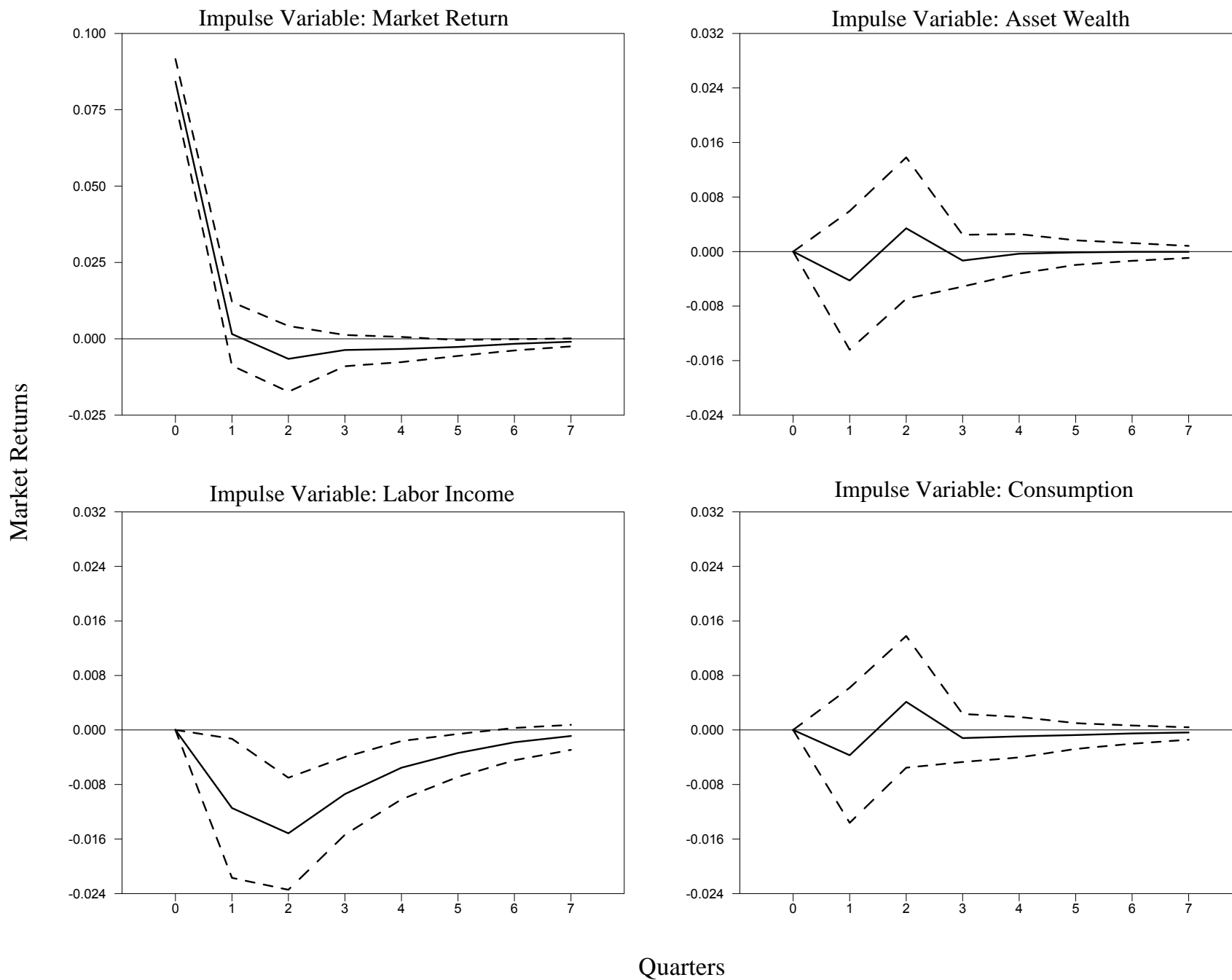
Table 6: Statistics on Predicting Average Returns for Betas from Different Factor Models

Model	<i>GMM with identity weighting matrix</i>							<i>Efficient GMM</i>				
	R^2	<i>Coefficients</i>						<i>Coefficients</i>				
		α	b_1	b_2	b_3	χ^2_*	$Dist^*$	α	b_1	b_2	b_3	$J\text{-test}^*$
<i>Panel A: Fama-French 25 value weighted portfolios</i>												
CCAPM	0.24	0.012 (0.008)	89.3 (54.9)			2.3 (0.126)	1.42 (0.000)	0.023 (0.005)	54.8 (22.3)			50.4 (0.001)
F&F	0.73	0.030 (0.013)	-2.19 (2.68)	3.14 (2.10)	3.10 (2.17)	10.2 (0.017)	0.65 (0.000)	0.033 (0.011)	-2.60 (2.44)	3.80 (2.10)	2.63 (1.94)	42.5 (0.004)
L&L	0.70	0.020 (0.012)	-20.6 (37.7)	3.7 (28.4)	8751 (3961)	6.2 (0.104)	0.75 (0.000)	0.026 (0.006)	-38.1 (17.0)	66.6 (28.4)	2067 (2099)	46.8 (0.001)
<i>lr</i>	0.81	0.015 (0.017)	27.7 (22.7)	10.3 (106.8)	18162 (5233)	14.4 (0.002)	0.70 (0.000)	0.022 (0.007)	40.9 (22.7)	-21.6 (40.4)	2259 (3184)	49.5 (0.000)
<i>lr & cay</i>	0.86	0.014 (0.010)	-28.4 (27.4)	-88 (63.4)	19026 (5998)	13.4 (0.004)	0.57 (0.000)	0.024 (0.007)	27.0 (27.4)	-74 (37.4)	4543 (4126)	42.2 (0.004)
<i>Panel B: Fama-French 25 equally weighted portfolios</i>												
CCAPM	0.24	0.010 (0.011)	89.3 (58.4)			2.8 (0.095)	1.42 (0.000)	0.031 (0.006)	54.8 (27.4)			50.4 (0.001)
F&F	0.78	0.047 (0.013)	-5.07 (2.90)	4.93 (2.04)	2.27 (2.43)	15.1 (0.002)	0.68 (0.000)	0.038 (0.010)	-2.26 (2.25)	2.78 (2.04)	2.66 (1.96)	49.4 (0.000)
L&L	0.78	0.033 (0.010)	-53.6 (32.5)	22.8 (29.9)	7287 (3357)	8.9 (0.031)	0.72 (0.000)	0.037 (0.005)	-39.6 (17.8)	81.0 (29.9)	3081 (2131)	48.2 (0.001)
<i>lr</i>	0.91	0.020 (0.019)	73.0 (26.1)	28.5 (97.6)	20897 (9363)	6.8 (0.080)	0.54 (0.000)	0.024 (0.006)	62.8 (26.1)	-62.7 (28.5)	4298 (4272)	42.0 (0.004)
<i>Panel C: Portfolios formed on Cash-flow/Price</i>												
CCAPM	0.01	0.017 (0.008)	81.6 (41.6)			3.9 (0.050)	2.13 (0.000)	0.025 (0.006)	43.5 (27.3)			45.4 (0.000)
F&F	0.55	-0.002 (0.031)	-8.0 (7.0)	8.1 (7.7)	9.3 (4.8)	5.9 (0.116)	0.74 (0.000)	0.013 (0.028)	-5.5 (7.0)	4.8 (7.0)	8.9 (4.3)	32.3 (0.000)
L&L	0.70	0.024 (0.016)	-12.5 (68.3)	-16 (56.4)	13724 (7166)	6.3 (0.096)	0.65 (0.223)	0.028 (0.012)	-23.3 (68.3)	-16 (45.1)	17483 (6473)	10.4 (0.107)
<i>lr</i>	0.72	-0.001 (0.017)	-52.0 (89.0)	-165 (88.4)	25005 (9640)	8.8 (0.032)	0.72 (0.120)	0.018 (0.018)	-74.3 (89.0)	-177 (126.2)	25798 (18757)	5.9 (0.435)
<i>Panel D: Industry portfolios</i>												
CCAPM	-0.48	0.023 (0.005)	-8.4 (37.4)			0.1 (0.822)	1.23 (0.000)	0.021 (0.004)	-18.4 (34.2)			15.2 (0.055)
F&F	0.13	0.021 (0.013)	-2.3 (4.9)	0.1 (3.7)	-3.5 (2.7)	2.8 (0.428)	0.63 (0.000)	0.016 (0.012)	-2.4 (4.9)	1.1 (3.5)	-3.9 (2.5)	10.2 (0.115)
L&L	-0.28	0.015 (0.009)	-17.1 (41.4)	30 (32.7)	-691 (4100)	1.2 (0.758)	0.77 (0.000)	0.017 (0.006)	-15.6 (41.4)	27 (21.6)	-2811 (3601)	11.6 (0.072)
<i>lr</i>	0.24	0.026 (0.009)	61.0 (44.7)	41 (65.1)	9494 (10056)	3.0 (0.395)	0.62 (0.000)	0.024 (0.007)	18.6 (44.7)	13 (52.0)	7507 (7487)	10.0 (0.123)

Note: Newey-West corrected standard errors in brackets under the estimated coefficients. GMM with a prespecified weighting replicates the Fama-MacBeth point estimates by using an identity matrix for the moments corresponding to expected returns and "very high" weights on the diagonal for the remaining moments. Efficient GMM iterates to convergence.

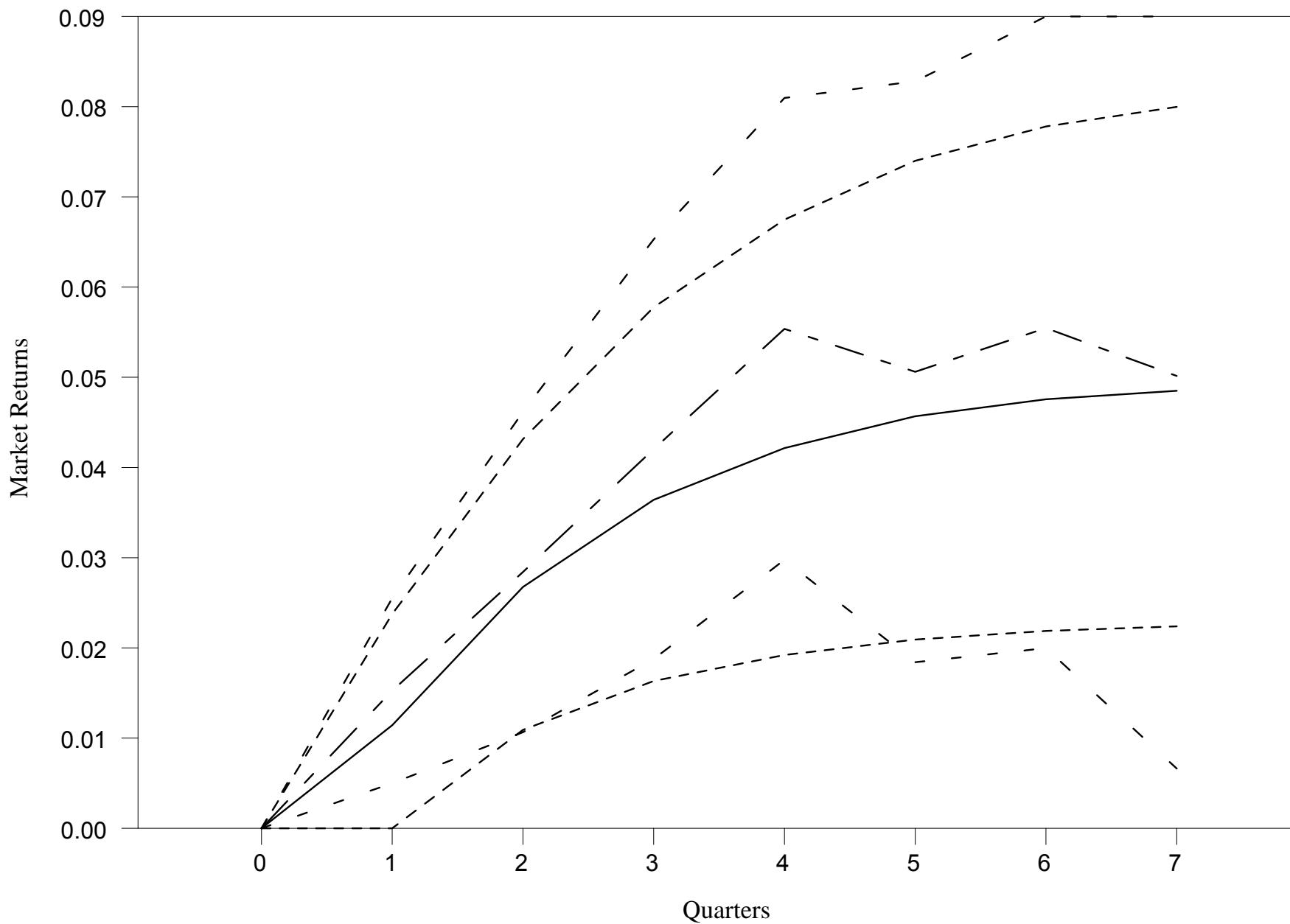
* p -values in brackets.

Figure 1: Impulse-Response Functions of Market Return



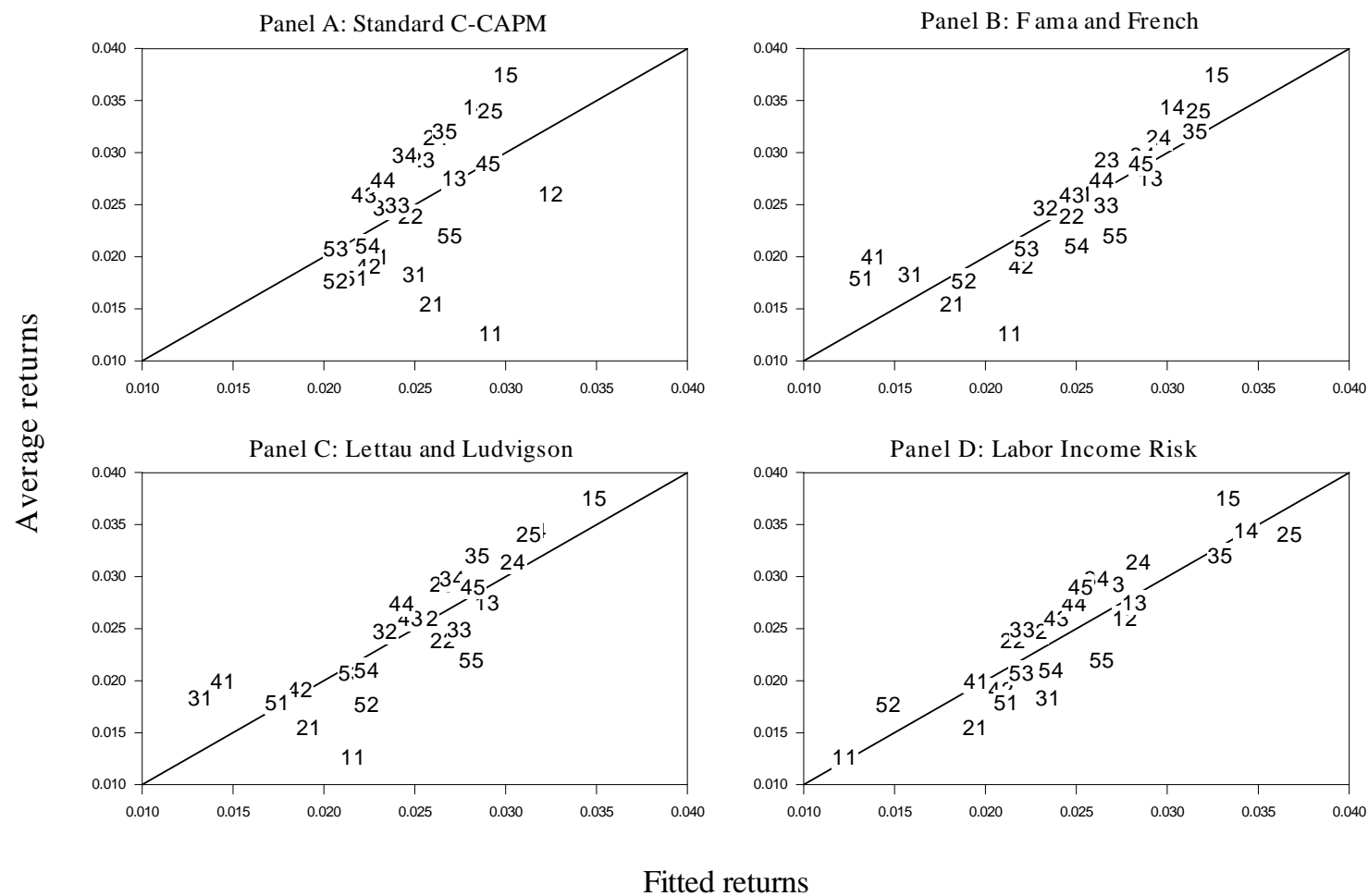
Note: Dashed lines represent 90% confidence bands

Figure 2: Long Run Effect of a Negative Labor Income Shock on Market Returns



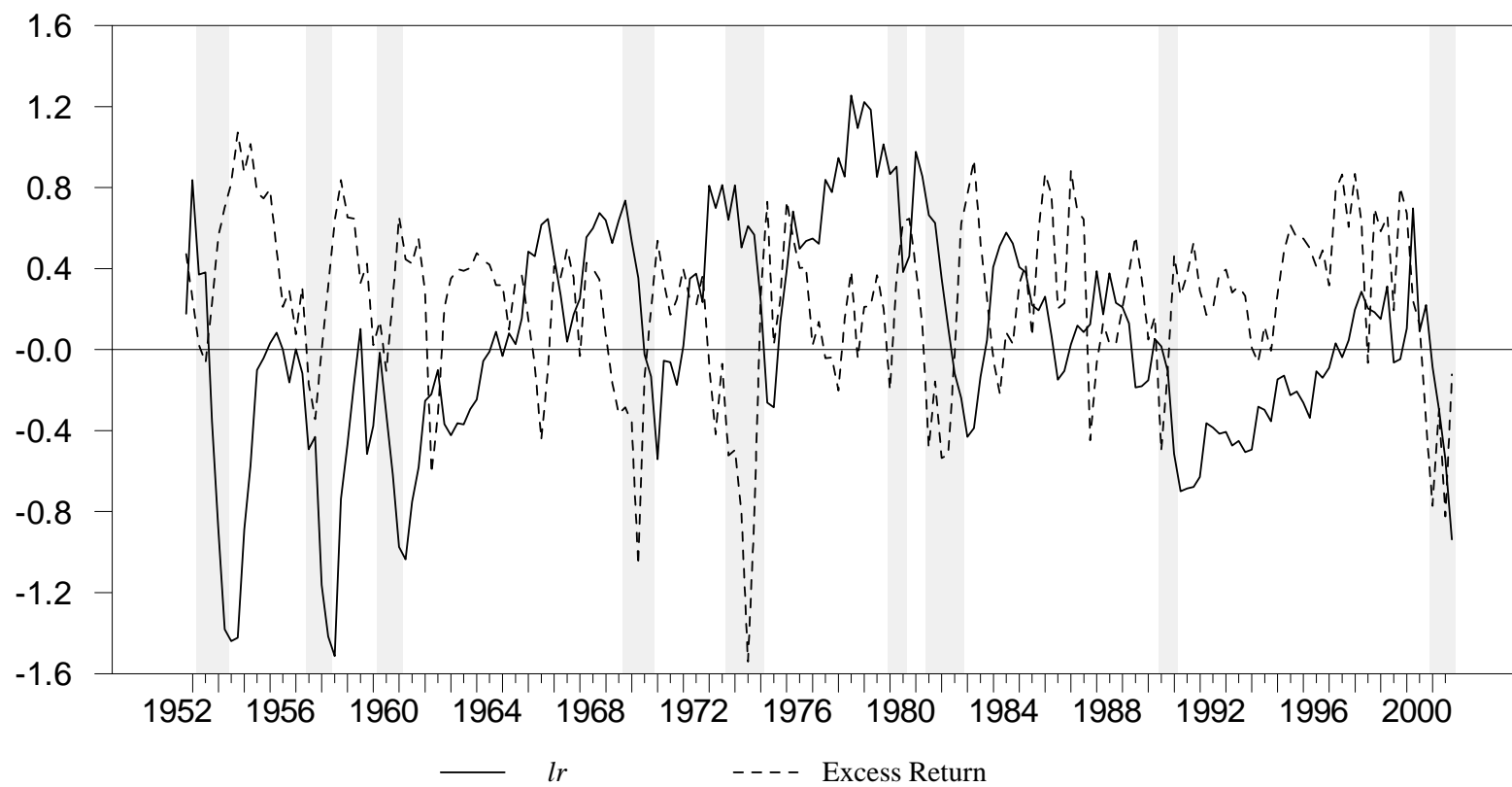
— VAR cumulative effect - - - - VAR 95% confidence bands
- - - OLS predicted effect - . - OLS 95% confidence bands

Figure 3: Comparison of Linear Factor Models of Expected Returns



Note: All returns are quarterly rates. Each portfolio is denoted by the rank of its market equity and then the rank of its ratio of book value to market value. Fitted values are based on the model estimates in Table 6.

Figure 4: Times Series of lr and Stock Market Excess Return



Note: Shaded areas are NBER recessions.

Table A2: F -tests and Measures of Fit of VAR Estimations of the Market Return Forecasting Equation

<i>VAR in first differences</i>					<i>VAR in levels</i>					
Number of lags:	1	2	3	4	Number of lags:	1	2	3	4	
R^2	0.06	0.08	0.11	0.14		0.06	0.09	0.13	0.18	
\bar{R}^2	0.04	0.04	0.05	0.06		0.04	0.06	0.07	0.10	
Independent variables:	r	0.86	0.82	1.15	1.67	r	0.21	0.13	1.02	2.24
		[0.356]	[0.441]	[0.332]	[0.158]		[0.651]	[0.880]	[0.385]	[0.066]
	Δy	6.50	5.31	5.10	2.75	y	9.96	6.31	6.49	7.61
		[0.012]	[0.006]	[0.002]	[0.030]		[0.002]	[0.002]	[0.000]	[0.000]
	Δa	0.51	0.48	0.90	1.64	a	0.98	0.95	1.69	2.94
	[0.477]	[0.620]	[0.443]	[0.165]		[0.323]	[0.388]	[0.170]	[0.022]	
Δc	0.56	0.74	0.56	0.70	c	2.88	0.29	0.70	0.93	
	[0.454]	[0.479]	[0.643]	[0.594]		[0.092]	[0.748]	[0.555]	[0.449]	

Significance levels in brackets under the F -statistics.

Figure A1: Response of Market Return to a Labor Income Shock (VAR in Levels)

